

ENTREPRENEURIAL VALUE CREATION: THREE ESSAYS
EXAMINING HOW ENTREPRENEURS CREATE VALUE
UNDER CONDITIONS OF UNCERTAINTY

by

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ABSTRACT

This dissertation consists of three essays examining how entrepreneurs create value under conditions of uncertainty. The first essay theoretically examines the process of stakeholder enrollment through which entrepreneurs acquire critical resources for their endeavors under informational conditions of risk and uncertainty. The second essay uses text-based analysis methodologies to empirically examine how far entrepreneurial mobile application developers attempting to create value do, and should, pivot in response to performance feedback. The third essay uses text-based analysis methodologies to empirically examine the optimal level of differentiation from the prototypical and exemplar category members for apps published by de novo mobile application developers.

This dissertation is dedicated to my patient and understanding wife, Mandy, my fun-loving children Ellie, Cameron, and Spencer, and my parents, Brad and Julie.

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CHAPTER 1

INTRODUCTION

There is growing interest among entrepreneurship and strategic management scholars in developing a deeper understanding of how value can be created through the introduction of new products and services. This dissertation contains three essays which examine several different aspects of the value creation process in the context of entrepreneurship.

The first essay theoretically examines entrepreneurial stakeholder enrollment. Most entrepreneurial endeavors do not initially possess all of the resources they need to successfully create a valuable opportunity. Some of the needed resources can be acquired through simple contracts. However, other resources require the resource provider to provide a level of effort that goes beyond that which is contractible. Such efforts often require the resource provider to form deep psychological bonds with the entrepreneurial endeavor. Stakeholder enrollment is the process of forming these bonds with entrepreneurial endeavors. The target of these bonds can be either the entrepreneur herself or the entrepreneurial opportunity being pursued. In entrepreneurial settings, these bonds are typically formed under conditions of risk or uncertainty. Under both risk and uncertainty, information about the entrepreneur's experience, reputation, personality, trustworthiness, charisma, and leadership style is available to stakeholders. However, one

important difference between these conditions is that, under risk, information about the value of the opportunity is available to stakeholders whereas under uncertainty, this information is not available. Thus, this essay first proposes that under conditions of risk, the initial target with which a stakeholder forms psychological bonds can be the entrepreneur, the opportunity, or a combination of both. The essay then proposes that under conditions of uncertainty, the initial target with which a stakeholder forms psychological bonds should be the entrepreneur—not the opportunity. These propositions generate important implications for scholars and practitioners alike. For example, one practical implication is that under conditions of uncertainty, the opportunity is likely to evolve and change substantially during the creation process. If stakeholders enroll in an uncertain opportunity (instead of enrolling in the entrepreneur), then each time entrepreneurs engaged in a “pivot,” they would have to re-enroll stakeholders. This implication leads directly into the second essay.

The second essay empirically examines entrepreneurial pivoting. Pivoting is widely believed to be an important ingredient for entrepreneurial success under conditions of uncertainty. However, it remains unclear how far entrepreneurs do—and should—pivot to improve their chances of successfully creating value. This essay draws on problemistic search and resource-based theory to empirically examine entrepreneurial pivoting in the context of the Google Play app store. This empirical context allows for the construction of a continuous measure of pivot distance using text-based analysis. Consistent with problemistic search theory, the lower the performance (installs) of a developer’s first app, the further the developer will pivot for its second app. And, consistent with resource-based theory, pivot distance negatively moderates the

relationship between app one installs and app two installs. Further analysis reveals that this moderating effect of pivot distance takes an inverted-u form: minor pivots outperform major pivots and not pivoting at all. Taken together, these findings suggest that app development entrepreneurs tend to “over-pivot” in response to negative performance feedback and that over-pivoting has a negative effect on performance. These findings highlight the need for caution when advising entrepreneurs to pivot without noting the potentially harmful effects of pivoting too far.

The third essay empirically examines how entrepreneurial organizations competing on a two-sided platform can position new products to maximize value creation. Platforms, such as internet search engines, Amazon, Netflix, Uber, Airbnb, video game consoles, YouTube, eBay, iTunes, and the Google Play app store are important competitive environments in today’s economy. At least two arguments for how a de novo organization should position its new products on platforms can be derived from the extant literature. On the one hand, some work suggests that entrepreneurs should conform by positioning new products in a way that is similar to other products in a market category to obtain the benefits of legitimacy. On the other hand, another body of work suggests that entrepreneurs should differentiate by positioning new products in a way that is different from other products to obtain a competitive advantage. As a result, de novo organizations competing on a two-sided platform often face uncertainty regarding how to position their products within a market category. Furthermore, prior work does not clearly articulate which other products within a market category should be used as reference points when making this conformity versus differentiation decision. This essay argues that there are two important judgment devices that organizations can

use to strategically categorize themselves within product market categories: the prototypical category member and the exemplar category member. Using a unique dataset from the Google Play mobile application store, this essay finds that the optimally distinct point for a de novo developer's first app is at low levels of similarity to the prototypical app, but at high levels of similarity to an exemplar app. Moreover, the essay finds that prototype similarity negatively moderates the positive effect of exemplar similarity such that the more an organization aligns with the prototype, the more the organization loses the competitive advantage gained from similarity to the exemplar. The findings have important implications for our understanding of competitive dynamics within and across product markets, strategic positioning at the time of market entry, and the interdependence of strategic categorization decisions.

CHAPTER 2

ENROLLING STAKEHOLDERS UNDER CONDITIONS OF RISK AND UNCERTAINTY¹

Introduction

Entrepreneurs often need resources they do not control in order to form and exploit opportunities (Cooper, Woo, & Dunkelberg, 1989). These resources range from financial to human capital, from technical and marketing expertise to accounting capabilities, and from direct social ties to indirect networks and affiliations (Freeman, 1984). Some of these resources can be obtained through simple contracts between an entrepreneur and the stakeholders who control these resources (Argyres & Mayer, 2007). However, other resources can be acquired only when those providing them are more deeply committed (Klein, Molloy, & Brinsfield, 2012) to an entrepreneurial endeavor (Shane, 2000). In entrepreneurial settings, the process of creating this deeper level of commitment can be called *stakeholder enrollment*.

A substantial literature describes the various types, antecedents, and outcomes of commitment in established organizations (Klein et al., 2012; Meyer & Herscovitch, 2001). However, none of this previous literature has examined the special challenges associated with inducing commitment in entrepreneurial settings. These challenges

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reflect, among other things, the informational context within which enrollment occurs. For example, recent research has identified two informational settings that have an important impact on the opportunity-formation process—risk (where decision makers know the possible outcomes of their choices and the probability of those outcomes) and uncertainty (where decision makers know neither the possible outcomes nor their probability) (Alvarez & Barney, 2007a). It may well be the case that the process of enrolling stakeholders in entrepreneurial endeavors varies depending on whether a setting is risky or uncertain.

The purpose of this article is to examine how the process of enrolling stakeholders varies as a function of the informational setting within which an entrepreneur is operating—risky or uncertain. The theory developed here suggests that different approaches to enrollment will be more or less effective depending on whether an entrepreneur is operating under conditions of risk or uncertainty. The article also suggests that under conditions of risk, the ability of entrepreneurs to analyze and describe opportunities will have a significant impact on their ability to enroll key stakeholders, while under conditions of uncertainty, the enrollment process cannot be based on the attributes of opportunities, but instead must be based on the attributes of the entrepreneur, e.g., his/her charisma, trustworthiness, and reputation.

The article begins by examining the concept of stakeholder enrollment and then suggests that the process of enrollment—both the bases upon which entrepreneurs enroll stakeholders and the timing of the enrollment process—varies depending on the informational context within which an entrepreneur is operating. The article generates a series of testable propositions and concludes with a discussion of the implications of

these propositions for a variety of issues in the field of entrepreneurship—including the theory of the entrepreneurial firm. In sum, this article addresses three important theoretical gaps in the literature: (1) the role of enrollment in acquiring certain critical resources for an entrepreneur; (2) how the enrollment process varies between conditions of risk and uncertainty; and (3) the relationship between entrepreneurial enrollment and more traditional research on organizational commitment (Klein et al., 2012).

Stakeholder Enrollment

The concept of stakeholder enrollment is closely related to the concept of workplace commitment (Klein et al., 2012). However, where workplace commitment examines the causes and consequences of psychological bonds of individuals to various aspects of an established workplace, stakeholder enrollment focuses on these bonds in entrepreneurial settings, where workplaces may not yet exist.

Commitment to existing workplaces

An extensive literature has explored the psychological bonds or attachments that individuals form with organizations, groups, individual leaders, projects, goals, or even abstract concepts within the workplace (Klein et al., 2012; Meyer & Herscovitch, 2001), as well as the antecedents (Basu & Green, 1997; Becker, 1992; Cheng, Jiang, & Riley, 2003; Ferris et al., 2003; Guthrie & Hollensbe, 2004; Hollenbeck & Klein, 1987; Johnson & Yang, 2010; Lok, Westwood, & Crawford, 2005; Silverthorne, 2004) and consequences (Hollenbeck & Klein, 1987; Klein, Wesson, Hollenbeck, & Alge, 1999; Mathieu & Zajac, 1990; Meyer, Becker, & Vandenberghe, 2004; Meyer, Stanley,

Herscovitch, & Topolnytsky, 2002; Rich, Lepine, & Crawford, 2010) of such bonds.

Klein et al. (2012), for example, identify four types of psychological bonds that individuals can form with a target in the workplace, each with different behavioral implications: acquiescence (when bonds form because individuals see few other options), instrumental (when bonds form because individuals calculate that such bonds reduce the risks associated with prior investments), commitment (when individuals choose to dedicate themselves to the success of the target), and identification (when individuals merge their identity with the identity of a target). The first two types of bonds—acquiescence and instrumental—lead to mostly in-role behaviors with minimal extra-role behaviors. The last two types of bonds—commitment and identification—are generally associated with higher levels of extra-role behaviors. In this literature, extra-role behaviors are defined as discretionary acts that go ‘above and beyond the call of duty’ when stakeholders provide resources to a target (Meyer & Herscovitch, 2001). In-role behaviors, however, refer to a series of expected actions typically contracted for in advance.

Despite the diverse theoretical and empirical literature on the psychological bonds that underpin workplace commitment, to date, this work has focused on understanding these phenomena only in the context of established workplaces (Becker, 2012). In particular, the causes and consequences of these bonds in entrepreneurial settings have yet to be addressed. This is the case even though entrepreneurs often need access to stakeholder resources they do not control and even though extra-role behaviors associated with higher levels of commitment may be important if stakeholders are going to make their resources available to entrepreneurs under conditions of risk or uncertainty. This

article focuses on these issues.

Enrollment in entrepreneurial settings

It is often the case that the same kinds of deep psychological bonds that emerge between an individual and an established workplace can also emerge between stakeholders and an entrepreneurial endeavor. When such bonds exist and when they help an entrepreneur gain access to critical resources, the stakeholder who has made these resources available is said to be *enrolled* in this entrepreneurial endeavor.

Of course, entrepreneurs can acquire many of the resources they need from actors who have not formed any deep psychological bonds with an entrepreneurial endeavor. For example, fuel for an entrepreneur's delivery van can be secured through a simple market exchange without forming such bonds. Moreover, the first two types of bonds identified by Klein et al. (2012)—acquiescence and instrumental bonds—do not involve deep psychological commitments and, thus, do not typically lead to important stakeholder extra-role behaviors. In this sense, those with these psychological bonds with an entrepreneurial endeavor can be thought of as only weakly enrolled.

However, there are times when all that must be done for a stakeholder to make resources available to an entrepreneurial endeavor cannot be specified *ex ante*. Sometimes, for example, stakeholders and those associated with an entrepreneurial endeavor may not know precisely which resources will be most valuable for that endeavor, when those resources need to be made available, how they might need to be modified, and so forth. In these settings, stakeholder actions to make resources available to an entrepreneurial endeavor must, by definition, involve extra-role behaviors because,

in this setting, all the relevant roles and responsibilities in this exchange are yet to be fully specified.

Work on organizational commitment suggests that these extra-role behaviors are likely only when stakeholders have strong psychological bonds with an entrepreneurial endeavor—including commitment and identity bonds (Klein et al., 2012). Stakeholders with these deep psychological bonds can be thought of as being strongly enrolled in an entrepreneurial endeavor. Moreover, these deep psychological bonds, to the extent that they are valuable and rare, may also be a source of sustained competitive advantage. Because of their socially complex nature, it may be difficult for others to imitate them at a low cost (J. Barney, 1991).

Enrollment targets

Of the many targets of the psychological bonds to existing workplaces identified in the organizational behavior literature (Becker, 2012; Klein et al., 2012; Meyer & Herscovitch, 2001; Reichers, 1985), two are particularly important in an entrepreneurial enrollment setting: the individual entrepreneur and the entrepreneurial opportunity. An individual entrepreneur is an example of a leader as the target of these psychological bonds (Klein et al., 2012). In practice, an *entrepreneur* might be a single individual or a small team with whom stakeholders form psychological bonds. An entrepreneurial opportunity is an example of an abstract concept as a target of these bonds (Meyer & Herscovitch, 2001).

Alvarez and Barney (2007) define an opportunity as competitive imperfections in product or factor markets. However, when stakeholders are enrolled to an entrepreneurial

endeavor, whether or not these competitive imperfections actually exist is typically not known with certainty. In this sense, the psychological bonds that emerge between stakeholders and an opportunity focus more on the potential for competitive imperfections, rather than the existence of these imperfections.

Theory Development

Prior work has identified a variety of activities that entrepreneurs can engage in to gain access to the resources they need to form and exploit opportunities. For example, Aldrich (1999) and others (Davidsson & Honig, 2003; P. W. Roberts & Sterling, 2012; Shane & Cable, 2002) show that entrepreneurs can use their direct and indirect social ties to attract employees and secure external financial investments. Also, entrepreneurs can use their business plans (Brinckmann, Grichnik, & Kapsa, 2010; Delmar & Shane, 2003), secured intellectual property (E. B. Roberts, 1991; Shane & Stuart, 2002), external accreditations and endorsements (Drori & Honig, 2013; Zott & Huy, 2007), and their willingness to invest their own funds in a project (Carter & Van Auken, 1990; Gartner, Frid, & Alexander, 2012) to obtain the resources needed to form and exploit an opportunity. In addition, entrepreneurs can use a variety of financial incentives (Arcot, 2014; Gompers & Lerner, 1999; Kaplan & Strömberg, 2003; Kotha & George, 2012; Ravid & Spiegel, 1997) and communication strategies to gain access to these resources (Cable & Shane, 1997; Cornelissen & Clarke, 2010; Parhankangas & Ehrlich, 2014).

However, this prior work has failed to distinguish between access to resources that requires simple contracts or weak form enrollment, on the one hand, and strong form enrollment on the other hand. This work has also failed to examine the impact of the

informational context of an entrepreneurial endeavor on the enrollment process.

Risk and uncertainty

The distinction between risk and uncertainty was first introduced by Knight (1921). Knight defined an informational setting as risky when those making decisions in the setting did not know, for sure, how a decision would turn out, but did know the possible outcomes associated with a decision and the probability of those different outcomes occurring. An uncertain informational setting, however, is a setting where the decision maker cannot know the possible outcomes and, thus, cannot know the probability of these outcomes occurring. In an entrepreneurial context, risk and uncertainty exist about whether or not an opportunity exists, the actions required to form and exploit that opportunity, the entrepreneurial skills required to form and exploit an opportunity, the potential for that opportunity to generate economic profits, and so forth.

Stakeholder enrollment under risk

Rarely are the outcomes of entrepreneurial endeavors known with certainty *ex ante*. Thus, in this sense, stakeholder enrollment typically takes place in conditions that are at least risky. Under conditions of risk, information about both the opportunity and the ability of the entrepreneur to exploit that opportunity does exist, but only probabilistically. Thus, for example, under conditions of risk, the possible outcomes associated with an opportunity, and their probabilities, can be known *ex ante*, but not the level of return an endeavor will actually generate. Moreover, while stakeholders can often directly observe some things about an entrepreneur, such as his/her experience,

reputation, personality, trustworthiness, charisma, and leadership style (Gupta, MacMillan, & Surie, 2004), they can know only probabilistically whether or not these attributes of the entrepreneur will enable that entrepreneur to exploit a particular opportunity.

Even though the outcomes associated with enrolling under risk can only be known probabilistically, it is nevertheless possible for stakeholders to develop psychological bonds with both opportunities and entrepreneurs in these settings. Stakeholders develop these bonds with opportunities when they develop a sense of commitment and identity with an opportunity, even if the full dimensions of that opportunity are not yet known. Stakeholders develop these bonds with entrepreneurs when they develop a commitment and identity with entrepreneurs even when their ultimate success (or failure) cannot be known with certainty. These observations lead to the first proposition.

Proposition 1: Under conditions of risk, the target of stakeholder enrollment can be the opportunity, or the entrepreneur, or both.

Later, it will be shown that Proposition 1 does not hold under conditions of uncertainty.

It follows from Proposition 1 that the enrollment process may begin with the entrepreneur as a target or with the opportunity as the target. This is because, under risk, at the time enrollment takes place, stakeholders can have some information about an opportunity or some information about an entrepreneur. These observations lead to Proposition 2:

Proposition 2: Under conditions of risk, stakeholder enrollment may begin with the opportunity as a target or with the entrepreneur as a target.

As with Proposition 1, it will be shown that Proposition 2 does not hold under conditions of uncertainty.

Stakeholder enrollment under uncertainty

Of course, not all entrepreneurial settings are risky. When neither the possible outcomes associated with a decision nor the probability of those outcomes is known, a decision-making setting is uncertain (Knight, 1921). Stakeholder enrollment is very different under conditions of uncertainty compared to conditions of risk.

Even under conditions of uncertainty, stakeholders can still know some things about the attributes of an entrepreneur. For example, a prospective stakeholder can often directly observe an entrepreneur's experience, reputation, personality, trustworthiness, charisma, and leadership style.

However, stakeholders cannot know, even probabilistically, whether these attributes of an entrepreneur will enable him/her to exploit a particular opportunity—because the opportunity in this uncertain setting does not yet exist. In uncertain settings, Alvarez and Barney (2007) suggest that entrepreneurs engage in actions to endogenously create the opportunities they ultimately exploit. One of the challenges entrepreneurs face in this setting is that in order to act in ways that ultimately may create an opportunity to be exploited, they may need resources they themselves do not control. Thus, to act to create an opportunity, entrepreneurs need to enroll important stakeholders, and they must do this before the opportunity they will ultimately exploit is known, even probabilistically. Such opportunities are cocreated through the joint actions of entrepreneurs and enrolled stakeholders. Only after engaging in these actions does an

opportunity emerge with dimensions that can be known or measured probabilistically.

It follows that to enroll stakeholders before the nature of entrepreneurial opportunities are understood, entrepreneurs must rely on attributes of themselves, as individuals, independent of the impact these attributes might ultimately have on their ability to exploit an opportunity. This can happen in at least two ways (Alvarez & Barney, 2005). First, entrepreneurs can seek to enroll stakeholders with whom they already have prior trusting relationships. Trust is important in this context because entrepreneurs are typically asking stakeholders to make specific investments in them—investments that generate the potential for opportunism on the part of entrepreneurs (Williamson, 1985). And because of uncertainty, the sources of this threat of opportunism cannot be known *ex ante* and, thus, appropriate contractual protections cannot be devised. In this setting, enrolling stakeholders who already have prior trusting relationships with an entrepreneur set aside opportunism concerns, which can enable an entrepreneur to get access to the resources needed to create an opportunity.

Second, stakeholders may become willing to invest in an entrepreneur in this setting because of that entrepreneur's charisma (Dobrev & Barnett, 2005). There is a substantial literature in sociology and organizational behavior on the ability of dynamic and charismatic individuals to enroll others in highly uncertain enterprises (Bass & Riggio, 2005; Weber, 1949). Charismatic leaders are able to enroll stakeholders by conveying a compelling vision of how the future might be created (Alvarez & Barney, 2005). Charisma is, therefore, likely to be particularly effective under conditions of uncertainty (Weber, 1949).

These observations lead to the following proposition:

Proposition 3: *Under conditions of uncertainty, the entrepreneur, and not the opportunity, is the target of stakeholder enrollment.*

Note that entrepreneurs, under conditions of uncertainty, are not likely to abandon their efforts to describe the opportunities they believe they are going to exploit as a way to enroll stakeholders. However, given uncertainty, the nature and dimensions of this opportunity are likely to change dramatically as entrepreneurs create it. If stakeholder enrollment relied only on these descriptions of opportunities, then each time entrepreneurs engaged in a ‘pivot’ (Arteaga & Hyland, 2013), they would have to re-enroll all their key stakeholders. Some re-enrollment is probably likely whenever the espoused opportunity is changed. But with trust and charisma in place, this enrollment process is much simpler post-pivot than would be the case if enrollment were based solely on attributes of the espoused opportunity.

This logic has an important impact on the processes by which enrollment takes place. For example, because entrepreneurs cannot reliably anticipate the return potential of opportunities under conditions of uncertainty, they cannot use the opportunity as the target of enrollment. This means that, under uncertainty, enrollment in an opportunity must come after enrollment in an entrepreneur. This logic leads to the last proposition:

Proposition 4: *Under conditions of uncertainty, enrollment in an entrepreneur precedes enrollment in an opportunity.*

Evolution of uncertainty and risk

Of course, uncertain situations can evolve into risky situations. This can happen as entrepreneurs gain additional information about the opportunities they are seeking to

exploit. Risky situations may also evolve into uncertain situations. This can happen when changes in technology, consumer tastes, or other environmental conditions generate settings where neither the possible outcomes associated with a decision nor their probability can now be known *ex ante*.

The fact that the informational conditions associated with an opportunity can change suggests that enrollment processes that enable access to resources during one time period may actually reduce the chances for success in another time period. For example, entrepreneurs who are very skilled at enrolling stakeholders under conditions of risk may find those same skills to be less effective if a risky situation becomes uncertain. The same is true for those skilled in these activities under conditions of uncertainty who find themselves under conditions of risk. Thus, the skills that can make an entrepreneur successful in enrolling stakeholders under conditions of uncertainty—including personal charisma and the ability to learn quickly and pivot—may be ineffective as the decision-making situation evolves from uncertainty to risk. This may be one reason it is not uncommon for sources of later stage funding to insist that founders—individuals with uncertainty-appropriate enrollment skills—be replaced by more professional managers—individuals with more risk-appropriate enrollment skills—as the informational context of an opportunity changes (Hellmann & Puri, 2002).

Discussion

This article began by acknowledging the importance of stakeholder enrollment in the success of entrepreneurial endeavors. The article then reviewed the information conditions of risk and uncertainty under which entrepreneurs commonly operate and

developed a series of propositions. These general arguments fill several important theoretical gaps in the literature and have a variety of implications for the study of entrepreneurship, for the practice of entrepreneurship, and for related academic disciplines.

Implications for entrepreneurship process research

Much entrepreneurship research focuses on the attributes of entrepreneurs (Nicolaou, Shane, Cherkas, Hunkin, & Spector, 2008) or entrepreneurial organizations (Lumpkin & Dess, 1996) and the implications of these attributes for a variety of entrepreneurial outcomes—including survival, the level of innovation, profitability, and so forth. Relatively less attention has been focused on the processes that link the attributes of entrepreneurs and entrepreneurial organizations with entrepreneurial outcomes. The process of enrollment, contingent on the informational context an entrepreneur is operating in, is largely determinative of entrepreneurial outcomes.

Enrollment under risk focuses on the attributes of the opportunity to be exploited, the valuable, rare, and costly to imitate capabilities of the entrepreneur, or both. Under conditions of risk, the process of enrollment to an opportunity may precede enrollment to an entrepreneur, or vice versa. Both these conclusions depend on information about the opportunity and/or the entrepreneur being known, probabilistically, *ex ante*.

Under conditions of uncertainty, enrollment in an entrepreneur precedes enrollment in an opportunity and builds on prior trusting relationships and the personal charisma of an entrepreneur. Thus, in this setting, stakeholders enroll—with the entrepreneur as the target—before the opportunity they will ultimately exploit is known,

even probabilistically.

Of course, the enrollment process is more difficult to study than the attributes of entrepreneurs and entrepreneurial organizations, on the one hand, and entrepreneurial outcomes on the other hand. However, these processes are the underlying causal mechanisms that link inputs to outputs and, thus, their study is essential to enhancing our understanding of entrepreneurial performance, broadly defined.

Not surprisingly, the emphasis on process also implies an emphasis on the social underpinnings of entrepreneurial activities. Much of the current entrepreneurship research focuses on the implications of technological innovation. The theory developed in this article suggests that such innovation is, in fact, an outcome of an entrepreneurial process of enrolling the stakeholders needed to exploit that opportunity. In this sense, technological innovation is the effect of an entrepreneurial process, not the cause of that process or the cause of entrepreneurial outcomes.

And the stakeholder enrollment process—especially under conditions of uncertainty—grows out of deeply social roots. Enrollment under uncertainty builds on trusting social relations and charismatic leadership. In this sense, it is the essentially social elements of relationships that make technological innovation possible, especially under conditions of uncertainty. That is, the study of entrepreneurship—especially under uncertainty—is the study of how social groups are formed, how they evolve, and, ultimately, how they perform.

Implications for the theory of the entrepreneurial firm

Discussion of the process of enrolling critical stakeholders in order to form and exploit an opportunity link the theory developed here with broader questions about the entrepreneurial theory of the firm, i.e., when entrepreneurial firms will be formed, what their size and scope will be, etc. Under conditions of risk, most extant theories of the firm—including transactions cost economics (Williamson, 1985), incomplete contract theory (Hart & Moore, 1990), and resource-based theories of the firm (Conner, 1991)—seem likely to apply. This is because under conditions of risk, enrollment in an opportunity may precede enrollment to an entrepreneur, or vice versa. This means that the enrollment process unfolds in a setting where the value of an opportunity can be known, at least probabilistically, and, thus, that many of the transactional hazards that might be associated with collaborating with an entrepreneur to exploit an opportunity can also be known *ex ante*, at least probabilistically. In this setting, decisions about whether or not to create a firm can be based on knowable threats of opportunism (consistent with transactions cost logic), knowledge about who has the most to gain from a particular transaction (consistent with incomplete contracts logic), and knowledge about who has the most valuable, rare, and costly to imitate capabilities (consistent with resource-based logic). Under risk, all this information can be known, probabilistically, *ex ante*, and appropriate decisions about firm boundaries can be made.

This is not likely to be the case under conditions of Knightian uncertainty. Under uncertainty, the value of a transaction is not known *ex ante* and, thus, potential sources of opportunism in exploiting that opportunity cannot be known *ex ante*. Under uncertainty, the thing that is not known is who has the most to gain from an opportunity; the value,

rarity, and inimitability of resources and capabilities cannot be known either. Under Knightian uncertainty, an entirely different basis for forming an entrepreneurial firm may be required.

Alvarez and Barney (2005) show that transactions cost and incomplete contracts theories of the firm can be modified to apply under conditions of Knightian uncertainty. However, the implications of these modifications for our understanding of how entrepreneurial firms arise—if they arise—have not yet been fully discussed. The arguments developed in this article parallel Alvarez and Barney (2005) in their emphasis on trusting prior relationships and entrepreneurial charisma which, taken together, may ultimately lead to the creation of a theory of the entrepreneurial firm (under uncertainty) as opposed to the theory of the entrepreneurial firm (under risk).

Implications for workplace commitment research

Although the term *enrollment* is not used, organizational behavior scholars provide insight about the psychological bonds that individuals form with various targets in the workplace. In particular, organizational behavior scholars consider different types of bonds that vary in degree of psychological involvement or emotional and cognitive association. All types of psychological bonds between an individual and a target can be weak or strong. Although the role of psychological bonds in entrepreneurial settings has yet to be studied, the theory developed in this article suggests that different approaches to enrollment will be more or less effective depending on whether the entrepreneur is operating under conditions of risk or uncertainty.

It can be difficult to facilitate the development of a particular type of bond even

under conditions of risk. This challenge is exacerbated under conditions of uncertainty where neither the possible outcomes associated with a decision nor the probability of those outcomes is known. Indeed, it is this uncertainty that excludes instrumental bonds (Klein et al., 2012) from consideration as *enrolled*—or at best only *weakly enrolled*—in uncertain entrepreneurial endeavors.

The entrepreneur's challenge under uncertainty, then, is to develop strong—identification or commitment (Klein et al., 2012)—bonds between stakeholders and some aspect of their entrepreneurial endeavor. Moreover, this article suggests that under uncertainty, this target must be, at least initially, the entrepreneur. This is because the entrepreneur needs stakeholders who are willing to make resources available in order to create opportunities and, thus, cannot use opportunities to enroll those stakeholders. It is through these strong bonds that stakeholders engage in extra-role behaviors crucial to an entrepreneurial endeavor.

Implications for precommitment

The arguments presented in this article also have important implications for the concept of precommitment (Sarasvathy, 2001). In her (2001) work, Sarasvathy states that precommitments from stakeholders are an important way to help entrepreneurs reduce uncertainty and establish barriers to entry. According to this view, entrepreneurs do not sell a predetermined vision or goal to stakeholders but instead allow stakeholders who choose to make precommitments to participate in the shaping of the entrepreneurial endeavor (Sarasvathy, 2008). Thus, precommitments are a way that stakeholders can make resources available to entrepreneurs creating opportunities.

But why do these stakeholders precommit? This article develops a theory of why stakeholders may precommit to an entrepreneurial endeavor—precommitments are the result of strong psychological bonds that can emerge between stakeholders and entrepreneurial endeavors, i.e., the stakeholder enrollment process is the cause of precommitment. The theory developed here also suggests what the targets of enrollment might be (i.e., the opportunity or the entrepreneur) and how this process is likely to change under conditions of risk versus uncertainty.

There is little doubt that precommitment, as discussed by Sarasvathy (2008), is important in many entrepreneurial settings. But understanding why stakeholders might precommit, who (or what) they might precommit to, and how the process of precommitment varies in different informational settings is central to understanding the cocreation and exploitation of entrepreneurial opportunities.

Empirical implications

The propositions derived from the theory developed in this article are inherently testable. Future empirical work will need to identify conditions that are risky and conditions that are uncertain and then examine the process by which enrollment occurs in these different settings and the outcomes of these processes. It is likely that this research will include both quantitative and qualitative dimensions—the quantitative to measure, for example, the outcomes of the enrollment process, and the qualitative to examine the process of enrollment (Alvarez & Barney, 2013; Alvarez, Young, & Woolley, 2015).

Implications for entrepreneurial practice

These arguments also have important implications for entrepreneurial practice. First, they suggest that there is no ‘one best way’ of doing entrepreneurship. While it is possible for enrollment in an opportunity to precede enrollment in an entrepreneur under conditions of risk, stakeholder enrollment to an entrepreneur precedes enrollment to an opportunity under conditions of uncertainty. While focusing on the attributes of the opportunity and/or entrepreneur in order to enroll stakeholders is perfectly reasonable under conditions of risk, using preexisting trusting relationships and personal charisma to enroll people under conditions of uncertainty is perfectly reasonable under conditions of uncertainty. Any prescription that fails to recognize these informational contingencies seems destined to be misleading, at least some of the time.

Of course, this article has examined just one contingency that can have an impact on the efficacy of entrepreneurial processes—risk versus uncertainty. It seems likely that many other such contingencies exist for entrepreneurs. Ultimately, the advice given to entrepreneurs and the content of the class material students read, need to be much more contextual than is often the case.

CHAPTER 3

ENTREPRENEURIAL PIVOTING

Introduction

There is increasing interest among scholars (Grimes, 2018; Navis & Ozbek, 2016; Teece, 2014) and practitioners (Blank & Dorf, 2012; Ries, 2011) in the role “pivoting” plays in the development of entrepreneurial endeavors. Although the term has yet to be precisely defined, pivoting logic suggests that because entrepreneurship is often an uncertain undertaking (Alvarez & Barney, 2010; Alvarez, Barney, & Anderson, 2013), entrepreneurs are likely to receive negative performance feedback (Eggers & Song, 2015; Hall & Woodward, 2010). When they receive negative feedback, this logic suggests that entrepreneurs must pivot by making changes to products, strategies, and/or business models to improve performance (Navis & Ozbek, 2016; Ries, 2011; Teece, 2014). Thus, this logic implies that pivoting is often an essential element of entrepreneurial success.

Unfortunately, absent an empirical measure of pivot distance, it remains unclear how far entrepreneurs do—and should—pivot. Moreover, extant theory fails to provide clear answers, particularly with regard to how far entrepreneurs should pivot to improve their chances of success. On the one hand, problemistic search theory suggests that the lower an endeavor’s initial performance is, the more distant its subsequent search (i.e., pivot) will be (Baum & Dahlin, 2007; Cyert & March, 1963; Desai, 2016; Greve, 1998;

Levinthal, 1997; March & Simon, 1958). This literature further implies that such a response is optimal: distant, nonlocal search (called “major pivots” in this paper) should be particularly beneficial to low-performing endeavors in rugged search landscapes (Baum & Dahlin, 2007; Cyert & March, 1963; Desai, 2016; Greve, 1998; Levinthal, 1997; March & Simon, 1958). On the other hand, resource-based theory implies that major, unrelated pivots will often fail to exploit any potentially valuable knowledge, capabilities, or other resources an endeavor may have developed in its early efforts (J. Barney, 1991; Chatterjee & Wernerfelt, 1991; Peteraf, 1993; Wernerfelt, 1984). Instead, “minor pivots” that are related to the endeavor’s early efforts should increase the chances of success more than major pivots.

The purpose of this paper is to empirically examine how far entrepreneurs do, and should, pivot in the context of the Google Play mobile application store. This context enables the creation of a pivot distance measure. Using text-based analysis (Hoberg & Phillips, 2010), a continuous measure of product pivot distance is constructed by determining how different a development endeavor’s second app is from its first app. This measure reliably enables the calculation of product pivot distance both within and between app developers and shows that developers tend to make distant, major product pivots.

The paper first hypothesizes and provides evidence that an endeavor’s initial performance and pivot distance are negatively related. The probability of a major product pivot decreases from 51.1% to 40.9% depending on whether a developer’s first app has 100 or 10,000 installs, respectively. This finding, coupled with the observation that the average first app has 100 installs, helps explain developers’ tendency to make distant,

major product pivots. Thus, app developers generally behave in a way that is consistent with problemistic search theory's implication that the lower the initial performance, the greater the pivot (Cyert & March, 1963; March & Simon, 1958).

The paper then develops a set of competing hypotheses to explore how pivot distance moderates the relationship between an endeavor's initial performance and its post-pivot performance. Consistent with resource-based theory (J. Barney, 1991; Wernerfelt, 1984), it is first shown that pivot distance negatively moderates the positive relationship between first app installs and second app installs. Further analysis reveals that the moderating effect of pivot distance takes an inverted-u form. Minor product pivots are associated with higher second app installs than major pivots or not pivoting in any meaningful way. Developers that make minor product pivots publish second apps that have up to 3.8 times more installs than developers that make major product pivots and up to 2.4 times more installs than developers that do not pivot in any meaningful way. Thus, consistent with problemistic search theory (Cyert & March, 1963; March & Simon, 1958), some degree of pivoting is beneficial. However, consistent with resource-based theory (J. Barney, 1991; Wernerfelt, 1984), pivoting too far can have harmful effects.

Together, these findings show that app developers tend to "over-pivot" in response to negative performance feedback and that over-pivoting has a negative effect on future performance outcomes. Thus, this paper cautions against advising entrepreneurs to pivot without noting the potentially harmful effects of pivoting too far.

Theory and Hypotheses

Prior work on pivoting

Entrepreneurial pivoting was popularized by Eric Ries' (2011) book *The Lean Startup*. In his book, Ries develops a lean startup methodology through which entrepreneurs experiment, learn, pivot, and experiment again until they eventually (hopefully) succeed. He defines a pivot as “a structured course correction designed to test a new fundamental hypothesis about the product, strategy, and engine of growth” (Ries, 2011, p. 149). Thus, Ries' work argues that fundamental (i.e., major) pivots can systematically improve an entrepreneur's odds of success. This perspective has been widely adopted by the popular press (Arteaga & Hyland, 2013; Blank & Dorf, 2012; Chapman, 2012; Furr & Ahlstrom, 2011; McGinn, 2012; Zwilling, 2011) and the university classroom (Blank, 2013).

Interest in entrepreneurial pivoting is also growing in the scholarly literature (Al-Aali & Teece, 2014; Bhawe, Rawhouser, & Pollack, 2016; Burns, Barney, Angus, & Herrick, 2016; Grimes, 2018; Navis & Ozbek, 2016; Pontikes & Barnett, 2015, 2016; Teece, 2014; Toft-Kehler, Wennberg, & Kim, 2016; Vogel, 2016). For example, recent work on dynamic capabilities suggests that pivoting is critical to success in the volatile environments that often characterize entrepreneurship (Al-Aali & Teece, 2014; Teece, 2014). And, in their work on entrepreneurial personality traits, entry, and opportunity realization, Navis and Ozbek (2016) suggest that pathways to success are clouded by the uncertainty that often characterizes entrepreneurship (Alvarez & Barney, 2007). Because of this uncertainty, they suggest that success often hinges on entrepreneurs' ability to “substantively ‘pivot’ or radically transform how they enact opportunities” (Navis &

Ozbek, 2016). In general, prior scholarly work implies, like Ries (2011), that major pivots are often essential to entrepreneurial success.

Pivot distance definition

Although a precise definition of pivot distance has not yet been put forth, prior work suggests that since entrepreneurs commonly operate under uncertainty (Alvarez et al., 2013), their initial theories of value creation often turn out to be incorrect (Felin & Zenger, 2009). Entrepreneurs are likely to perceive the need to modify their current theory of value creation when their current theory is performing poorly or when they believe that a different theory would be more valuable, regardless of their current level of performance. One way in which entrepreneurs can modify their theories of value creation is to pivot, or make changes to their products, strategies, and/or business models (Navis & Ozbek, 2016; Ries, 2011; Teece, 2014).

It is important to note that the word pivot assumes a fulcrum—the fixed point around which a lever turns (Tipler & Mosca, 2007). In the case of entrepreneurial pivoting, the fulcrum can be thought of as an endeavor’s past products, strategies, and/or business models. Pivoting therefore implies *within* endeavor change. Changes made to products, strategies, and/or business models *between* endeavors (as in the serial entrepreneurship literature) are therefore not considered pivots.

Building on the points above, this paper defines pivot distance as *the degree to which an endeavor changes search direction relative to its most similar past product, strategy, and/or business model in an attempt to increase future performance*.

Thus, unlike prior work, this paper argues that pivoting is a continuous, rather

than a discrete choice. Entrepreneurs can choose to alter their search direction on a continuous scale ranging from 0 degrees (no pivot) to 90 degrees (orthogonal pivot), or anywhere in between as shown in Figure 3.1.

Of course, entrepreneurs may choose to keep pursuing their current, poorly performing theory or give up entirely instead of pivoting. However, this paper explicitly focuses on examining how far entrepreneurs do, and should, pivot—conditional on having chosen to pivot. The paper draws on problemistic search and resource-based theory to facilitate this examination. Although neither theory was developed to explain or predict pivoting, important implications for pivoting can be derived from both.

Problemistic search theory

Problemistic search theory suggests that the lower an endeavor's current performance, the more distant its subsequent search efforts will be (Cyert & March, 1963; March & Simon, 1958). In other words, the less valuable a current search location is to an endeavor, the more valuable distant search will appear to be. Thus, low performance can help endeavors overcome local search biases in favor of more distant, nonlocal search (Cyert & March, 1963; Levitt & March, 1988; March & Simon, 1958). The theoretical argument that past performance and search distance are negatively related has received considerable empirical support (Baum & Dahlin, 2007; Desai, 2016; Greve, 1998, 2003, 2008; Khanna, Guler, & Nerkar, 2016).

Problemistic search theory further suggests that distant, nonlocal search can help entrepreneurs avoid local optima in a rugged search landscape (Baum & Dahlin, 2007; Cyert & March, 1963; Desai, 2016; Greve, 1998; Levinthal, 1997; March & Simon,

1958). When an endeavor fails to discover a valuable peak at its initial search location, searching locally is presumed to lead to similarly low performance. By engaging in nonlocal search, an endeavor can increase its odds of discovering a valuable peak elsewhere. This increase in odds does not require the endeavor to possess distant foresight. It merely assumes that searching locally is likely to lead to similarly poor performance while searching nonlocally can at least lead to the same odds of discovering a valuable peak as a de novo entrant. Thus, this work suggests that increasing search distance improves expected future performance.

Resource-based theory

Resource-based theory does not explicitly articulate how far an entrepreneurial endeavor is likely to alter its search direction in response to negative performance feedback. Instead, this theory has most often been used to explain and predict how extant firms with resources of known value can gain and sustain competitive advantage (J. Barney, 1991; Chatterjee & Wernerfelt, 1991; Peteraf, 1993).

However, resource-based theory does suggest that related diversification should outperform unrelated diversification (J. Barney, 1991; Peteraf, 1993; Wernerfelt, 1984). This is because a firm's knowledge, capabilities, or other resources are more easily exploited when applied to a related, rather than an unrelated, context. By building on its existing resources, an endeavor may be able to increase its odds of creating a valuable opportunity near its previous search location. This theoretical argument has received considerable empirical support (Campa & Kedia, 2002; Chatterjee & Wernerfelt, 1991; Miller, 2006). Thus, this work suggests that the more related the diversification, the

higher the expected performance.

Hypotheses

The first hypothesis draws on problemistic search theory to answer the question: How far *do* entrepreneurs pivot? If product pivot distance is defined as the degree to which an entrepreneurial endeavor changes the search direction for its second product relative to its first product, then problemistic search theory implies that the lower the endeavor's initial performance is, the greater its pivot distance will be, on average. Thus,

Hypothesis 1. *The lower the performance of an entrepreneurial endeavor's first product, the further it will pivot for its second product.*

The second set of hypotheses seeks to answer the question: How far *should* entrepreneurs pivot? More specifically, these hypotheses seek to identify the moderating effect of pivot distance on future performance, assuming a positive relationship between initial and future performance. Thus, these hypotheses account for past performance—an important source of endogeneity when predicting future performance.

On the one hand, the problemistic search literature suggests that increasing search distance should improve expected future performance. However, it remains ambiguous at what point on a continuous scale search transitions from harmful local to beneficial nonlocal. Additionally, it remains unclear whether an increase in search distance within the nonlocal category would produce an increasingly positive effect or whether the benefits of nonlocal search are constant, provided the endeavor searches a sufficient distance away from the previous location. Thus, it is difficult to derive a precise hypothesis for the effect of pivot distance on future performance from this literature.

However, this work can be interpreted to imply that searching too locally can harm future performance outcomes and that there is little downside to searching too distantly. In other words, there should be a generally positive relationship between search distance and expected performance outcomes. If product pivot distance is defined as the degree to which an entrepreneurial endeavor changes the search direction for its second product relative to its first product, then problemistic search theory implies the following hypothesis,

Hypothesis 2a. *Pivot distance positively moderates the relationship between the performance of an entrepreneurial endeavor's first and second products.*

On the other hand, the resource-based literature suggests that the more related the diversification, the higher the expected performance. This is because an endeavor's valuable knowledge, capabilities, or other resources are more easily exploited when applied to a related, rather than an unrelated, context. However, in the case of a nascent entrepreneurial endeavor seeking to create value, it is unclear whether its resources are valuable or not, particularly when the endeavor initially performs poorly. Such an endeavor possesses only *potentially* valuable resources. Thus, it is also difficult to derive a precise hypothesis for the effect of pivot distance on future performance from this literature. However, this work can be interpreted to imply that unrelated diversification will often fail to exploit any potentially valuable resources an endeavor may have developed through its early efforts. Thus, resource-based theory implies that, for endeavors with potentially valuable resources, there is no downside to diversifying in too related a context but that diversifying in too unrelated a context can have a negative effect on performance. In other words, there should be a generally positive relationship

between relatedness and expected performance outcomes. To the extent that relatedness decreases with pivot distance, resource-based theory implies that,

Hypothesis 2b. *Pivot distance negatively moderates the relationship between the performance of an entrepreneurial endeavor's first and second products.*

An attempt to integrate the pivoting implications of problemistic search and resource-based theory reveals two key distinctions. First, problemistic search theory implies that making very small pivots (not pivoting in any meaningful way) should negatively affect expected future performance while resource-based theory implies the opposite. This implication of resource-based theory is potentially problematic. For example, resource-based theory seems to imply that introducing a *nearly identical* second product is the optimal strategy for an endeavor to increase its chances of success—even when the first product performed exceptionally poorly. This prediction of resource-based theory may be due, at least in part, to the fact that the theory does not provide much guidance on the question of why, or how far, entrepreneurs choose to pivot. Intuitively, and consistent with problemistic search theory, it seems reasonable to assume that the endeavor will recognize the need to search in a different location if it learns that its resources have little to no value in a specific context. In this case, resource-based theory could be interpreted to imply that the endeavor's resources are only potentially valuable if applied in a different, but still related, context. Drawing on this revised interpretation of resource-based theory, and the original interpretation of problemistic search theory: making minor (but still related) pivots should outperform making very small pivots (not pivoting in any meaningful way).

Second, problemistic search theory implies that endeavors cannot pivot too far

while resource-based theory implies that pivoting too far can negatively affect expected future performance. This implication of problemistic search is potentially problematic. For example, it seems to imply that the cost of sacrificed resource productivity is negligible when pivoting to a distant, unrelated search location in which an endeavor's existing knowledge, skills, capabilities, and resources are not at all applicable. Intuitively, and consistent with resource-based theory, it seems reasonable to assume that the endeavor may be better-served by leveraging at least some of its existing resources rather than discarding them completely and having to engage in the costly acquisition or development of all new resources when pivoting. Thus, it could be argued that making minor (but still related) pivots should outperform making very major, unrelated pivots.

Combining these two key distinctions between the problemistic search and resource based theories leads to the final hypothesis,

Hypothesis 3. Pivot distance moderates the relationship between the performance of an entrepreneurial endeavor's first and second products. The performance of an endeavor's second product increases with pivot distance, but only to a point, beyond which pivot distance has a negative effect on performance.

Methods

Data

The data source for this study is the Google Play app store (play.google.com/store/apps), the official mobile application store for phones and tablets running the Android operating system. Google Play is currently the world's largest app store in terms of number of apps offered and number of developers, generating tens of

billions of dollars in revenues annually (App Annie, 2017). Google Play publicly provides rich data for each app, including the number of downloads, review score, the number of reviews, product-market category, version updating history, and, importantly for this study, a complete text description for each app. These data were collected on nearly the entire contents of the Google Play app store 16 times between February, 2015 and September, 2016.

These data allow for the creation of an objective, comparable, and reliable measure of pivot distance. Using text-based analysis (Hoberg & Phillips, 2010), a continuous measure of product pivot distance is constructed by determining how different a developer's second app is relative to its first app. This setting also allows for the observation of the sequential pivoting actions of thousands of nascent app development endeavors within a single marketplace in a manner that is largely free from survivorship bias. Additionally, the setting enables the study of pivoting in a dynamic, volatile environment with a low cost of failure—precisely the type of setting in which pivoting is believed to be a particularly valuable strategy (Ries, 2011; Teece, 2014).

This study's sample consists of all first-time Google Play app developers that begin by publishing one app and subsequently publish at least one additional app during the data collection period. Only developers with “clean” data and developers that publish apps in the English language are included. The end result is a sample consisting of 170,544 app-month observations from a cohort of 10,369 first-time app development endeavors.

Measures

Dependent variables. *Pivot distance* is calculated by determining the distance between the text descriptions of a developer's first and second apps. This is done by using basic cosine similarity, a widely accepted method for calculating the similarity between two text documents (Hoberg & Phillips, 2010; Hoberg, Phillips, & Prabhala, 2014; Kwon & Lee, 2003). Basic cosine similarity measures the angular distance between two non-zero vectors. Thus, each app's text description must first be transformed into a word vector before cosine similarities can be calculated.

To create a vector for each app's text description, Python was used to identify each description's language, remove punctuation and numbers, remove stop words (e.g., the, a, and, etc.), remove non-English words, and stem words to their root (e.g., simulator, simulators, simulate, simulation, simulations, all stem to 'simul'). The end result of this natural language processing is a vector for each app comprised of a count of the number of times each word in an app's text description is used. For example, Table 3.1 shows the word vectors for the hypothetical app descriptions "The sky was bluer than blue in 1978" and "The sky was greyish blue in 1980."

The cosine similarity between two apps, A and B, is calculated using formula (1):

$$\frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (1)$$

In this formula, A represents the word vector for a developer's first app, B represents the word vector for the developer's second app, i represents each unique word used in the two apps' descriptions, and n represents the total number of unique words used in the two apps' descriptions.

In order to calculate the *pivot distance* between apps A and B, the basic cosine similarity is subtracted from one as shown in formula (2):

$$1 - \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (2)$$

Pivot distance ranges from 0.0 to 1.0. A score of 0.0 indicates that the developer's first and second app text descriptions are identical and that no pivot was made. A 1.0 indicates that the developer's first and second app text descriptions do not share any common words and that an orthogonal pivot was made. In the case of the example from Table 3.1, the *pivot distance* is 0.225 – suggesting a small pivot.

Major pivot is a dummy variable indicating whether *pivot distance* is above or below 0.850, the median pivot distance value.

App two installs is the number of installs a developer's second app had generated at the time it was last observed. Google Play provides data on how many times each app has been installed. These data are provided in categorical format, with 19 categories of app installs (e.g., 0, 1 to 5, 5 to 10, 10 to 50, ... 1 billion to 5 billion). To create this measure, the lowest number in the categorical installs range is identified, one is added to this number (to correct for cases with zero installs), and then this number is logged to account for skewness. For example, if Google Play reports that a developer's second app has 100 to 500 installs, *app two installs* would be coded as $\log(100 + 1) = 4.615$.

Independent variables. *App one installs* is the logged number of installs a developer's first app had the month before publishing its second app. The lower the installs of a developer's first app, the lower the performance (i.e., the more negative the performance feedback) is assumed to be. To the extent that past performance predicts

future performance, it is important to account for this source of endogeneity in models that predict app two installs.

Pivot Distance is also used as an independent variable to explain its effect on *app two installs*.

Control variables. This study also includes a number of control variables.

Description length is the logged count of characters in an app's cleansed description. *App size* is the size of an app in megabytes. *Free* is a dummy variable indicating whether the app is free (1) or not (0). *In-app* is a dummy variable indicating whether the app offers in-app purchases (1) or not (0). *App age* is the number of days since an app was originally published on Google Play. *Game* is a dummy variable indicating whether the app is a game (1) or not (0). *Time between apps* is the number of days between when the developer published its first app and its second app. *Second apps* is a count of the number of second apps a developer publishes simultaneously after publishing its first app.

Developer max apps is the maximum number of apps a developer ends up publishing during the data collection period. *Abandoned first app* is a dummy variable indicating whether a developer released a new version of its first app (1) or not (0) after publishing its second app. *Category switch* is a dummy variable indicating whether a developer's second app is in a category that is the same (0) or different (1) than its first app.

Controls for category effects using Google Play's 41 unique category classifications (at the time of this study) are included. The study also includes month fixed effects for each time data were collected from the Google Play app store.

Results

Descriptive statistics

Summary statistics for this study's measures are provided in Table 3.2 and correlations are provided in Table 3.3.

The distribution of *pivot distance* scores for the second apps included in this study is illustrated in Figure 3.2. The mean of the *pivot distance* distribution is 0.728 and the median is 0.850. The left hand side of the distribution contains a small bulge, representing cases where the developer's first and second apps are nearly identical, with pivot distances of less than 0.2. When interpreting *pivot distance*, cases with a value of 0.0 to 0.2 are called "no pivot." The middle of the distribution, ranging from 0.2 to 0.8500 (median), is called "minor pivot." And the right hand side of the distribution, ranging from 0.8500 (median) to 1.0, is called "major pivot." As shown in Figure 3.2, app developers in this sample tend to make distant, major pivots.

Figure 3.3 presents a kernel density plot of *app one installs*. This measure of installs is logged and is measured the month before publication of a developer's second app. The mean *app one installs* is 5.300 (200 installs), the median value is 4.615 (100 installs), and the maximum value is 16.118 (10 million installs). Thus, *app one installs* outcomes are highly skewed. Low first app performance (i.e., negative performance feedback) is a common occurrence in this study.

How far do entrepreneurs pivot?

To test the first hypothesis, ordinary least squares (OLS) and logistic regression are used to assess the effect of *app one installs* (initial performance) on *pivot distance*.

These results are presented in Table 3.4. Robust standard errors are clustered at the developer level. Multicollinearity is not an issue with VIF scores below 4.0. Model 1 introduces the control model and uses OLS regression to predict pivot distance. Model 2 adds the independent variable of *app one installs* to the OLS regression. Model 3 adds a measure of developer ability (discussed in the alternative explanations section below). Models 4 through 6 replicate models 1 through 3, but use logistic regression to predict the probability of making a major pivot.

As hypothesized, the coefficient for *app one installs* is negative in all of the models in Table 3.4. For example, Model 2 shows that a one unit increase in *app one installs* is associated with a 0.011 decrease in *pivot distance* ($p < 0.001$). Similarly, Model 5 finds that the relationship between *app one installs* and the binary *major pivot* measure is also negative ($\text{beta} = -0.102, p < 0.001$). A one unit increase in *app one installs* is associated with a 9.7% decrease in the probability of making a *major pivot*.

In order to aid in the interpretation of this nonlinear logistic regression (Hoetker, 2007), Figure 3.4 plots the marginal effects for Model 5 at different values of *app one installs*. The marginal effects indicate that a developer with *app one installs* of 4.6 (100 installs) has a 51.1% probability of making a *major pivot* while a developer with *app one installs* of 9.2 (10,000 installs) has a 40.9% probability of making a *major pivot*. Together, the models from Table 3.4 show that *app one installs* and *pivot distance* are negatively related and lend strong support to Hypothesis 1.

How far should entrepreneurs pivot?

To test Hypotheses 2a, 2b, and 3, ordinary least squares (OLS) regression is used to assess the moderating effect of *pivot distance* on *app two installs*, controlling for the positive main effect of *app one installs* on *app two installs*. This moderating effect is illustrated in Figure 3.5 which shows the hypothesized relationships between the key explanatory variables in this study. Table 3.5 presents the results for analysis of how far entrepreneurs should pivot in response to negative performance feedback. These models only include second apps that were listed on Google Play for 60 or more days to ensure that sufficient time passed to observe variation in second app performance outcomes. Robust standard errors are clustered at the developer level. To reduce the potential for multicollinearity in the interaction terms included in these models, the *app one installs* and *pivot distance* measures are mean-centered at 5.300 and 0.724, respectively. The *pivot distance squared* measure is the square of the mean-centered *pivot distance* measure. Multicollinearity is not an issue in these models, with VIF scores below 4.0. Model 1 introduces the control model which includes *app one installs* as a predictor of *app two installs*. Models 2 adds the *pivot distance* variable. Model 3 interacts the *pivot distance* and *app one installs* measures to show the moderating effect of *pivot distance* on *app two installs*. Models 4 and 5 use the binary measure *major pivot* instead of the continuous measure of *pivot distance*. Models 6 and 7 include the effects of *pivot distance* and *pivot distance squared* to test for the presence of a curvilinear relationship.

As expected, *app one installs* has a substantial and positive effect on *app two installs* in Model 1 (beta = 0.354, $p < 0.001$), as well as the rest of the models in Table 3.5. Past performance is an important predictor of future performance.

Consistent with Hypothesis 2b, and contrary to Hypothesis 2a, the interaction between *app one installs* and *pivot distance* is negative ($\beta = -0.109, p < 0.01$) in Model 3. In addition to this moderating effect, *pivot distance* also has a negative main effect on *app two installs* in Model 3 ($\beta = -0.275, p < 0.05$). Similarly, in Model 5, the interaction between *app one installs* and *major pivot* is negative ($\beta = -0.107, p < 0.001$) and the main effect of *major pivot* is also negative ($\beta = -0.295, p < 0.001$). Thus, *pivot distance* negatively moderates the relationship between *app one installs* and *app two installs*, as predicted by Hypothesis 2b.

And, consistent with Hypothesis 3, this moderating effect takes an inverted-u shape as shown in Model 7. Figures 3.6 and 3.7 aid in the interpretation of the effects from Model 7, given the complexities of interpreting the interactions in this model.

As shown in Figure 3.6, a mean-centered *pivot distance* of -0.224 (which translates to a raw *pivot distance* of 0.5, a minor pivot) is associated with higher *app two installs* than a *pivot distance* of -0.724 (raw *pivot distance* of 0.0, no pivot) or a *pivot distance* of 0.276 (raw *pivot distance* of 1.0, a major pivot) when logged, mean-centered *app one installs* is greater than -2.7 (which translates to 10 first app installs). When *app one installs* is below -2.7, major pivots outperform minor pivots, but the effect size is neither substantial nor meaningful.

Figure 3.7 is also derived from Model 7 and more clearly illustrates the inverted-u moderating effect of *pivot distance* on *app two installs*, for a particular level of *app one installs*. In this figure, the solid line represents an app developer that had -0.5 logged, mean-centered *app one installs* (100 installs). This developer would be expected to generate 5.366 *app two installs* (214 installs) if its mean-centered pivot distance was -

0.724 (raw pivot distance of 0.0, no pivot), 5.750 *app two installs* (314 installs) if its pivot distance was -0.224 (raw pivot distance of 0.5, minor pivot), and 5.226 *app two installs* (186 installs) if its pivot distance was 0.276 (raw pivot distance of 1.0, major pivot).

The dashed line in Figure 3.7 represents an app developer that had 1.8 logged, mean-centered *app one installs* (1,000 installs). This developer would be expected to generate 6.106 *app two installs* (449 installs) if its mean-centered pivot distance was -0.724 (raw pivot distance of 0.0, no pivot), 6.742 *app two installs* (847 installs) if its pivot distance was -0.224 (raw pivot distance of 0.5, minor pivot), and 5.810 *app two installs* (334 installs) if its pivot distance was 0.276 (raw pivot distance of 1.0, major pivot).

The solid line with the square marker in Figure 3.7 represents an app developer that had 4.1 logged, mean-centered *app one installs* (10,000 installs). This developer would be expected to generate 6.845 *app two installs* (939 installs) if its mean-centered pivot distance was -0.724 (raw pivot distance of 0.0, no pivot), 7.735 *app two installs* (2,287 installs) if its pivot distance was -0.224 (raw pivot distance of 0.5, minor pivot), and 6.392 *app two installs* (597 installs) if its pivot distance was 0.276 (raw pivot distance of 1.0, major pivot). In this case, a minor pivot would produce 2.4 times more installs than no pivot and 3.8 times more installs than a major pivot.

In sum, the results presented in Table 3.4 provide strong support for Hypothesis 1. The lower the *app one installs*, the further the *pivot distance*. This finding, coupled with the high probability of publishing a first app that has low *app one installs* (as shown in Figure 3.3), helps explain why app developers tend to make distant, major pivots (as

shown in Figure 3.2).

The results presented in Table 3.5 support the rejection of Hypothesis 2a in favor of Hypothesis 2b. *Pivot distance* negatively moderates the relationship between *app one installs* and *app two installs*. At a more detailed level, and consistent with Hypothesis 3, this moderating relationship takes an inverted-u shape. *App two installs* increase with *pivot distance*, but only to a certain point, after which increasing *pivot distance* has a negative impact on *app two installs*. Minor pivots outperform major pivots and not pivoting at all.

Post hoc: alternative explanations

Selection bias. It could be argued that the results in Models 2 and 5 of Table 3.4 are driven by selection bias if low ability developers who publish less successful apps are more likely to make major pivots than high ability developers. To account for this alternative explanation, Models 3 and 6 add a measure of developer ability measure to the OLS and logistic regressions. *Developer ability* measures a developer's ability to generate installs relative to its 10 closest competitors. This measure is constructed using basic cosine similarity and app text descriptions. The text description of a developer's first app is compared to the text descriptions of all extant apps in its same category. The average logged installs of the app's 10 nearest neighbors represents the "predicted" performance for a developer's first app. For example, if a developer's first app generated 6.2 logged installs (500 installs) and the average logged installs of its 10 nearest neighbors was 2.7 (100 installs), then this developer's ability would be $6.2 - 2.7 = 3.5$, suggesting that this is a high ability developer. If a developer's first app generated 6.2

logged installs (500 installs) and the average logged installs of its 10 nearest neighbors was 8.5 (5,000 installs), then this developer's ability would be $6.2 - 8.5 = -2.3$, suggesting that this is a low ability developer. This measure of *developer ability* complements the *app one installs* measure by identifying when a given number of installs, say 500, represents a good, bad, or average outcome.

Consistent with this alternative explanation, both models show that the lower the *developer ability*, the greater the *pivot distance* (beta = -0.006, $p < 0.001$ in Model 3; beta = -0.044, $p < 0.001$ in Model 6). However, both models also show that the negative main effect of *app one installs* on holds even when controlling for *developer ability* (beta = -0.008, $p < 0.001$ in Model 3; beta = -0.074, $p < 0.001$ in Model 6). In Model 6, a one unit increase in *app one installs* is associated with a 7.1% decrease in the probability of making a *major pivot* when controlling for *developer ability*. Although low ability developers are more likely to make major pivots than high ability developers, all developers are less likely to make a *major pivot* as *app one installs* increase. Thus, the main results hold even when controlling for this alternative explanation.

Major pivots and high second app installs. While Table 3.5 clearly shows that distant, major pivots are associated with lower *average* second app performance than minor pivots, it could be argued that major pivots might have a positive effect on a developer's odds of producing a *highly successful* second app. To investigate this alternative explanation, the models in Table 3.5 were replicated using *app two installs 100k* as the dependent variable. This variable is coded as a one if a second app had 100,000 or more installs at its last observation and a zero if not. Replication of Table 3.5 using logistic regression on *app two installs 100k* did not produce significant main or

moderating effects for any of the pivot distance measures. Given the difficulty of interpreting interaction terms—particularly nonlinear second order interaction terms—in logistic regressions (Hoetker, 2007; Zelner, 2009), Table 3.5 was also replicated using OLS regression on *app two installs 100k*. This OLS replication produced results that were substantially similar to those presented in Table 3.5 and suggest that distant, major pivots are negatively related to the probability of publishing a highly successful second app. Thus, these results do not contradict, and may even be largely consistent with the main average *app two installs* results presented in Table 3.5. Compared to minor pivots, major pivots do not increase, and may even decrease, the probability of publishing a second app with 100,000 or more installs. These replications are available upon request.

Robustness checks

These results are robust to a number of alternative specifications. For example, the results from Tables 3.4 and 3.5 hold when: the square root transformation is not applied to *pivot distance*, the *pivot distance* measure only allows each word in an app's description to be counted once, cases where *pivot distance* is equal to 1.0 are dropped, apps with a *description length* of less than 50 characters are dropped, developers with *second apps* greater than one are dropped, cases where *developer max apps* is greater than or equal to five are dropped, and cases where a developer's first app had more than 10,000 installs are dropped. Additionally, the logistic regression results are robust to splitting the *major pivot* measure at 0.60, 0.95, or anywhere in between.

The results from Table 3.5 are also substantively the same if ordered logistic regression is used instead of OLS. Additionally, these results hold if logged review count

is used in place of the categorical *app two installs* variable (these measures share a 0.89 correlation) in the OLS regressions. The results are also substantively the same when second apps less than 60 days old at the time they were last observed are included in the regression and when the independent variables are centered and standardized.

Discussion

This paper examines how far entrepreneurs do—and should—pivot in response to negative performance feedback in the context of the Google Play app store. The paper defines pivot distance and develops a measure of product pivot distance based on textual analysis of app descriptions. The paper draws on problemistic search and resource-based theory to develop its hypotheses. Consistent with problemistic search theory, the paper finds that the lower the installs of an entrepreneurial app developer's first app, the further the developer will pivot, on average, for its second app. This finding, coupled with the high likelihood of publishing a first app that has low installs, helps explain the tendency of app developers to make major product pivots.

The paper also finds that, consistent with resource-based theory, pivot distance negatively moderates the relationship between first app installs and second app installs. More specifically, this relationship takes an inverted-u form in which minor product pivots are associated with higher second app installs than major pivots and not pivoting in any meaningful way. This finding is consistent with problemistic search theory's implication that minor pivots should outperform not pivoting and consistent with resource-based theory's implication that minor pivots should outperform major pivots.

Taken together, these findings suggest that app development entrepreneurs tend to

“over-pivot” in response to negative performance feedback, and that over-pivoting has a negative effect on performance. These findings have important implications for scholars and practitioners alike.

Entrepreneurial pivoting

In general, prior work on entrepreneurial pivoting suggests that ‘fundamental,’ ‘substantial,’ or ‘radical’ (i.e., major) pivots are often an essential ingredient for success under conditions of uncertainty (Blank & Dorf, 2012; Navis & Ozbek, 2016; Ries, 2011; Teece, 2014). However, prior work relies on a handful of wildly successful, retrospective case studies and has yet to produce compelling empirical data in support of this suggestion.

This paper’s empirical findings tell a different story. By adopting a continuous measure of pivot distance, the paper shows that entrepreneurs can, and often do, pivot too far. Compared to minor pivots, major product pivots can actually decrease app development entrepreneurs’ odds of succeeding. Prescribing pivoting as a means of achieving entrepreneurial success under uncertainty, without noting the potentially harmful effects of pivoting too far, may not be sound advice. This caution is especially warranted given entrepreneurs’ tendency to make major pivots in response to the negative performance feedback that is all-too-common in entrepreneurial contexts (Eggers & Song, 2015; Hall & Woodward, 2010).

Problemistic search theory

This paper's findings lend support to problemistic search theory's suggestions that pivot distance should increase as performance decreases and that minor pivots should outperform not pivoting when initial performance is low (Cyert & March, 1963; March & Simon, 1958). By implementing a continuous measure of pivot distance, which is closely related to search distance, the paper is able to show how far from the initial search location entrepreneurs must pivot to capture the benefits of nonlocal search.

However, the paper also produces findings that contradict the implicit assumption in the problemistic search and strategic change literatures that nonlocal search is preferable to local search, or that more strategic change is better when an organization's performance is low (Baum & Dahlin, 2007; Desai, 2016; Greve, 1998, 2003, 2008). Much of this work only examines how much organizations change in response to negative performance feedback without considering what the performance implications of these strategic changes might be. This paper shows that nonlocal search is not necessarily superior to local search when initial performance is low—entrepreneurs can search too distantly. Instead, these findings lend support to closely related work which assumes that organizations lack 'distant foresight' and that they can increase their odds of success when they already possess most of the resources necessary to spot and seize local, nearby opportunities (Denrell, Fang, & Winter, 2003; Gavetti & Menon, 2016).

Resource-based theory

This paper's findings lend support to resource-based theory's argument that minor product pivots are more likely than major product pivots to exploit any knowledge,

resources, or capabilities an entrepreneurial endeavor may have developed as a result of its past experience (J. Barney, 1991; Campa & Kedia, 2002; Chatterjee & Wernerfelt, 1991; Miller, 2006; Peteraf, 1993; Wernerfelt, 1984). In this empirical context, minor, related product pivots improve future performance more than major, unrelated product pivots.

Importantly, this finding suggests that endeavors can create value by making minor pivots that leverage knowledge, resources, and capabilities of previously unproven value. In other words, even when an endeavor tries (and initially fails) to create value, it may develop *potentially* valuable knowledge, resources, and capabilities. And, according to related diversification logic, unlocking this potential value is more likely when these resources are redeployed in related, rather than unrelated, contexts (Chatterjee & Wernerfelt, 1991; Wernerfelt, 1984).

The paper's findings also suggest that resources and capabilities may be more important than pivoting, or learning strategies, to entrepreneurial success. These findings show that pivoting does not, on average, help low performing developers "catch up" to high performing developers. For example, a developer whose first app has 100 installs (reflecting low capabilities) would be expected to generate fewer second app installs than a developer whose first app had 100,000 installs (reflecting high capabilities), regardless of pivot distance. Thus, although pivot distance has substantial and significant effects for developers within a given capability level, pivoting does not, on average, lead to the development of superior capabilities. Thus, this paper questions the wisdom of advising entrepreneurs to fail fast and fail often (H. E. Aldrich & Kenworthy, 1999; Khanna et al., 2016; Sarasvathy, 2001). It may be the case that entrepreneurs operating under

uncertainty are more likely to learn how to fail than how to succeed as a result of their past failures.

Limitations and research opportunities

Although well-suited for the study of entrepreneurial product pivoting, the findings derived from the Google Play app store are not likely to generalize to all other settings. This dynamic, knowledge-based, high technology empirical context is characterized by low barriers to entry, low costs of failure, rapid development times, and short product life cycles. These findings may not generalize well to settings that differ on one or more of these dimensions. Additional work in different empirical contexts is needed to develop a more thorough understanding of the causes and consequences of pivoting.

This paper explicitly focuses on a particular type of pivoting: product pivoting. Thus, it remains unclear whether these findings generalize to other types of pivoting such as strategy pivoting or business model pivoting. Future work investigating the causes and consequences of different types of pivoting is therefore warranted.

In order to overcome endogeneity concerns, this paper focuses on the past performance of an entrepreneurial endeavor as the key driver of pivoting behavior and consequences. However, it may be the case that there are other explanatory variables that could broaden our understanding of entrepreneurial pivoting. For example, varying levels of demand and environmental uncertainty may affect pivoting behavior and outcomes in important ways. Exploring additional explanatory variables also has the potential to broaden our understanding of pivoting.

The paper purposefully excludes the examination of the pivoting behavior of established app development endeavors in favor of nascent, entrepreneurial endeavors. Future work could examine the causes and consequences of pivoting among established endeavors. Additionally, in order to facilitate the cleanest possible identification of pivoting causes and consequences, the paper only examined a developer's first two apps. Future work could also look at how an endeavor's pivoting behavior changes when it has more than a single past product around which it can pivot. This paper also intentionally excludes comparing the effects of pivoting to the effects of commitment strategies (updating the first app instead of publishing a second app) and pure exit strategies (neither updating the first app nor publishing a second). Future work exploring the relative effects of these different strategies could also prove fruitful.

Finally, this study's measure of performance, installs, may not be perfectly correlated with the amount of revenue an app generates. However, it seems reasonable to assume that installs and revenue are positively related. The more installs an app has, the more revenue-generating potential it can potentially generate through fees to install the app, advertisements inside the app, and in-app purchases. Future work can also build on this paper by more directly examining the financial causes and effects of pivoting.

Conclusion

Despite the growing popularity of entrepreneurial pivoting strategies, it remains unclear how far entrepreneurs do, and should, pivot. This paper finds that app development entrepreneurs tend to over-pivot in response to negative performance feedback and that over-pivoting has a negative effect on future performance outcomes.

Together, these findings suggest the need for caution when advising entrepreneurs to pivot as a means of achieving success without noting the potentially harmful effects of pivoting too far.

Table 3.1

Example word vectors

Hypothetical app description 1: "The sky was bluer than blue in 1978"

Hypothetical app description 2: "The sky was greyish blue in 1980"

	blue	grey	sky
App description #1 word vector	2	0	1
App description #2 word vector	1	1	1

Pivot distance = 0.225

Table 3.2
Summary statistics

Variable	App One: One Month Before Publishing App Two					App Two: Last Observation				
	mean	sd	min	max	n	mean	sd	min	max	n
Installs (Logged)	5.299	2.706	0.000	16.118	10,369	5.063	2.995	0.000	16.118	14,739
Description Length (logged)	5.976	0.894	2.303	8.374	10,369	5.799	0.950	2.303	8.281	14,739
App Size	12.775	16.877	0.000	100.000	10,302	12.811	16.021	0.000	100.000	14,687
Free	0.947		0	1	10,369	0.936		0	1	14,739
In-app	0.140		0	1	10,369	0.131		0	1	14,739
App Age	94.275	100.013	0.000	552.000	10,369	182.988	147.697	0.000	566.000	14,739
Game	0.289		0	1	10,369	0.315		0	1	14,739
Developer Ability	-0.214	2.622	-9.761	10.458	10,369	-0.285	2.610	-9.761	10.458	14,739
Pivot Distance						0.728	0.294	0.000	1.000	14,739
Time Between Apps						99.774	89.546	0.000	548.800	14,739
Second Apps						2.727	3.493	1.000	27.000	14,739
Developer Max Apps						5.526	6.327	2.000	62.000	14,739
Abandoned First App						0.681		0	1	14,739
Category Switch						0.552		0	1	14,739

Notes: There are 88,101 first app-month and 82,443 second app-month observations in the sample.

Table 3.3
Correlation coefficients

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 App Two Installs (logged)														
2 App One Installs (logged)	0.502													
3 Description Length (logged)	0.269	0.150												
4 App Size	0.106	0.070	0.166											
5 Free?	0.221	0.061	-0.080	-0.052										
6 In-app?	0.152	0.134	0.138	0.280	0.042									
7 App Age	0.337	-0.010	0.036	-0.031	-0.033	0.002								
8 Game?	0.082	0.085	0.063	0.395	0.058	0.308	-0.014							
9 Developer Ability	0.352	0.693	0.033	-0.008	0.047	0.057	0.149	-0.045						
10 Pivot Distance	-0.089	-0.141	-0.296	-0.087	0.204	-0.043	0.007	0.037	-0.087					
11 Time Between Apps	-0.100	-0.022	-0.059	0.013	0.013	0.012	-0.152	-0.105	0.172	0.040				
12 Second Apps	-0.050	0.019	0.102	0.006	-0.023	-0.082	-0.111	0.036	-0.064	-0.040	-0.153			
13 Developer Max Apps	0.060	0.063	0.098	-0.004	0.007	-0.050	0.036	0.039	0.011	-0.028	-0.157	0.733		
14 Abandoned First App?	-0.210	-0.247	-0.087	0.018	0.042	-0.029	-0.258	0.083	-0.272	0.148	0.049	-0.001	-0.079	
15 Category Switch	-0.032	-0.049	-0.090	-0.017	0.129	0.016	-0.014	0.097	-0.073	0.477	0.027	-0.026	-0.010	0.111

Notes: Correlations > 0.02 are significant at the $p < 0.05$ level. Correlations are for the last scrape of a developer's second app.

Table 3.4

Regressions on pivot distance and major pivot

Variable	OLS on Pivot Distance			Logit on Major Pivot		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
App One Installs (logged)		-0.011*** [0.001]	-0.008*** [0.002]		-0.102*** [0.011]	-0.074*** [0.014]
Developer Ability			-0.006*** [0.002]			-0.044*** [0.013]
Description Length (app one)	-0.021*** [0.004]	-0.017*** [0.004]	-0.017*** [0.004]	-0.201*** [0.032]	-0.166*** [0.033]	-0.170*** [0.033]
Description Length (app two)	-0.072*** [0.003]	-0.071*** [0.003]	-0.072*** [0.003]	-0.480*** [0.028]	-0.475*** [0.029]	-0.477*** [0.029]
App Size (app one)	-0.001** [0.000]	-0.000* [0.000]	-0.001*** [0.000]	-0.010*** [0.002]	-0.009*** [0.002]	-0.009*** [0.002]
Free (app one)	0.194*** [0.020]	0.223*** [0.020]	0.219*** [0.019]	0.751*** [0.114]	1.019*** [0.118]	1.077*** [0.118]
In-app (app one)	-0.002 [0.009]	0.008 [0.009]	0.002 [0.009]	0.029 [0.067]	0.111 [0.069]	0.112 [0.069]
Time Between Apps	0.000 [0.000]	0.000*** [0.000]	0.000*** [0.000]	0.001* [0.000]	0.002*** [0.000]	0.002*** [0.000]
Second Apps	-0.002 [0.003]	-0.003 [0.003]	-0.003 [0.003]	-0.017 [0.018]	-0.025 [0.019]	-0.026 [0.019]
Developer Max Apps	0.001 [0.001]	0.001 [0.001]	0.001 [0.001]	0.006 [0.008]	0.007 [0.008]	0.008 [0.007]
Abandoned First	0.078*** [0.008]	0.068*** [0.009]	0.055*** [0.008]	0.521*** [0.056]	0.439*** [0.058]	0.408*** [0.059]
Month Fixed Effects Included?	Yes	Yes	Yes	Yes	Yes	Yes
Category Effects Included?	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.019*** [0.038]	1.003*** [0.038]	1.060*** [0.044]	3.171*** [0.312]	3.102*** [0.314]	3.016*** [0.314]
Observations	14,693	14,693	14,693	14,693	14,693	14,693
R-squared	0.134	0.142	0.169			
Pseudo R-squared				0.097	0.106	0.107

Notes: Robust standard errors clustered at the developer level in brackets. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The app one measures are from the month before app two was published. The *app one installs* and *description length* measures are logged. Models 1-3 use OLS regression to predict the continuous measure of *pivot distance*. Models 4-6 use logit regression to predict the probability of a *major pivot* (distance ≥ 0.850).

Table 3.5
OLS regressions on app two installs

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
App One Installs (logged, centered)	0.354*** [0.018]	0.352*** [0.018]	0.346*** [0.019]	0.350*** [0.018]	0.394*** [0.020]	0.348*** [0.018]	0.388*** [0.020]
Pivot Distance (centered)		-0.298** [0.111]	-0.275* [0.111]			-1.085*** [0.170]	-1.114*** [0.170]
Pivot Distance Squared						-2.048*** [0.322]	-2.099*** [0.321]
App One Installs X Pivot Distance			-0.109** [0.040]				-0.327*** [0.058]
App One Installs X Pivot Distance Squared							-0.577*** [0.126]
Major Pivot				-0.293*** [0.060]	-0.295*** [0.060]		
App One Installs X Major Pivot					-0.107*** [0.023]		
Developer Ability	0.119*** [0.016]	0.118*** [0.016]	0.119*** [0.016]	0.118*** [0.016]	0.120*** [0.016]	0.118*** [0.016]	0.120*** [0.016]
Description Length (app one)	-0.119** [0.037]	-0.126*** [0.037]	-0.119** [0.037]	-0.132*** [0.037]	-0.124*** [0.037]	-0.144*** [0.037]	-0.136*** [0.037]
Description Length (app two)	0.773*** [0.034]	0.755*** [0.034]	0.753*** [0.035]	0.746*** [0.034]	0.743*** [0.035]	0.738*** [0.035]	0.736*** [0.035]
App Size (app two)	0.010*** [0.002]	0.009*** [0.002]	0.010*** [0.002]	0.009*** [0.002]	0.009*** [0.002]	0.009*** [0.002]	0.009*** [0.002]
Free (app two)	3.077*** [0.086]	3.122*** [0.088]	3.114*** [0.087]	3.104*** [0.085]	3.090*** [0.085]	3.069*** [0.087]	3.044*** [0.086]
In-app (app two)	0.309*** [0.084]	0.307*** [0.084]	0.304*** [0.085]	0.309*** [0.084]	0.294*** [0.084]	0.301*** [0.084]	0.282*** [0.084]
App Age (app two)	0.003*** [0.000]	0.003*** [0.000]	0.003*** [0.000]	0.003*** [0.000]	0.003*** [0.000]	0.003*** [0.000]	0.003*** [0.000]
Time Between Apps	-0.005*** [0.000]	-0.005*** [0.000]	-0.005*** [0.000]	-0.005*** [0.000]	-0.005*** [0.000]	-0.005*** [0.000]	-0.005*** [0.000]
Second Apps	-0.053* [0.021]	-0.053* [0.022]	-0.053* [0.022]	-0.053* [0.022]	-0.051* [0.022]	-0.052* [0.021]	-0.049* [0.021]
Developer Max Apps	0.031*** [0.009]	0.031*** [0.009]	0.031*** [0.009]	0.031*** [0.009]	0.032*** [0.009]	0.031*** [0.009]	0.031*** [0.009]
Abandoned First	-0.065 [0.062]	-0.054 [0.062]	-0.057 [0.062]	-0.048 [0.062]	-0.050 [0.062]	-0.044 [0.062]	-0.045 [0.062]
Category Switch	-0.176** [0.055]	-0.102 [0.064]	-0.113 [0.064]	-0.060 [0.061]	-0.068 [0.061]	-0.029 [0.063]	-0.032 [0.063]
Month Effects for App Two Included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category Effects Included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.460 [0.368]	-0.403 [0.369]	-0.467 [0.368]	-0.164 [0.371]	-0.229 [0.369]	-0.021 [0.369]	-0.074 [0.366]
Observations	10,711	10,711	10,711	10,711	10,711	10,711	10,711
R-squared	0.427	0.428	0.429	0.429	0.432	0.431	0.434

Notes. Robust standard errors clustered at the developer level in brackets. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. App one measures are from the month before app two was published. App two measures are from the time the app was last observed. The *app one installs*, *app two installs*, and *description length* measures are logged. The *app one installs*, *pivot distance*, and *pivot distance squared* measures are mean-centered. Only includes second apps that were listed on Google Play for 60+ days.

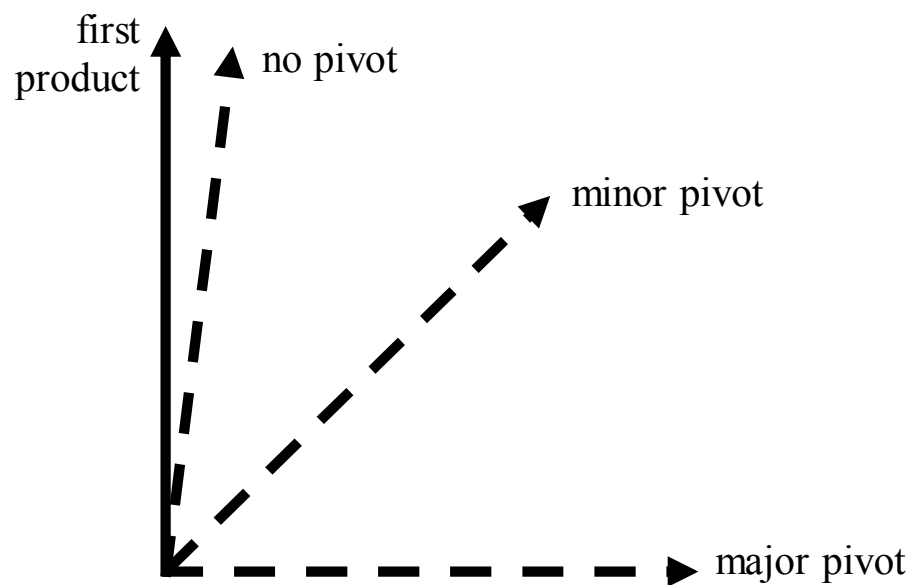


Figure 3.1 Pivot distance illustration.

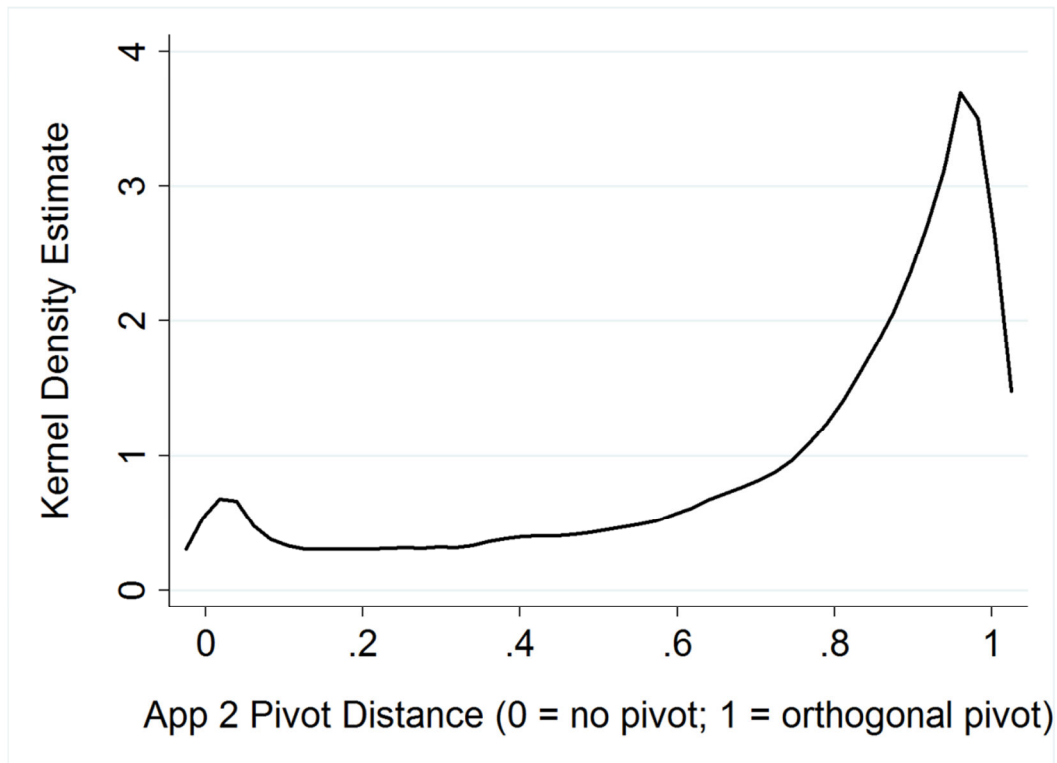


Figure 3.2 Kernel density plot of pivot distance scores. Kernel = epanechnikov, bandwidth = 0.0250. This measure of product pivot distance is derived from the basic cosine similarity between the text descriptions of a developer's first and second apps. Pivot distance can range from 0.0 (no pivot at all) to 1.0 (orthogonal, major pivot). This distribution has a mean of 0.728 and a median of 0.850. This distribution can be categorized as no pivot (0.00 to 0.200), minor pivot (0.200 to 0.850), and major pivot (0.850 to 1.000).

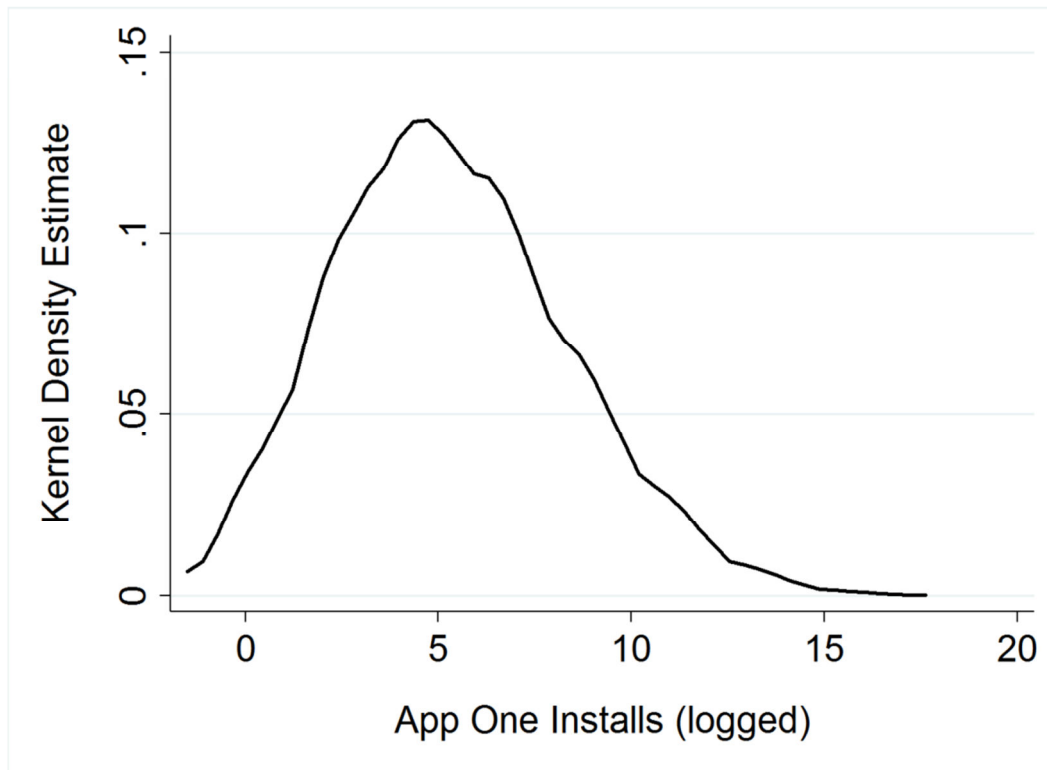


Figure 3.3 Kernel density plot of app one installs. Epanechnikov kernel, bandwidth = 1.5.

This histogram shows the distribution of developers' logged app one installs 1 month prior to publishing their second apps. The mean of this distribution is 5.300 (200 installs), the median is 4.615 (100 installs), and the maximum is 16.118 (10 million installs). Thus, low first app installs is a common occurrence among the developers in this study.

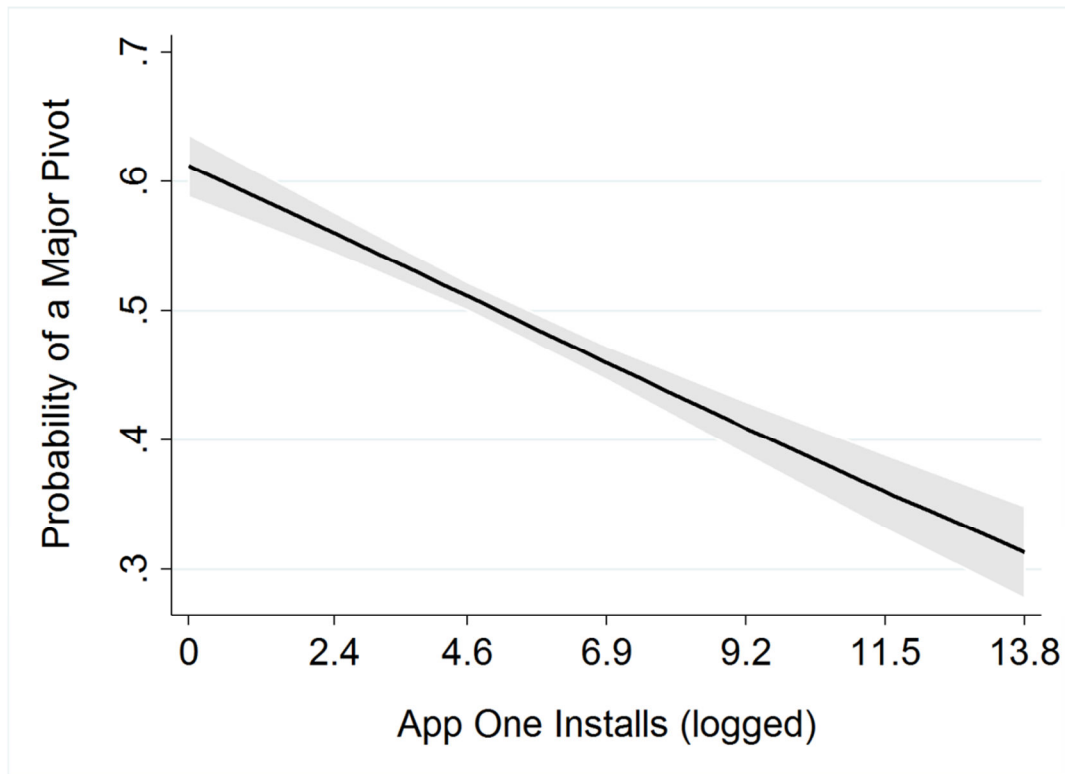


Figure 3.4 Probability of a major pivot by app one installs. In this figure, the logged app one installs of a developer's first app, 1 month before publishing its second app, is used to predict the probability of making a major pivot (pivot distance ≥ 0.850). The more successful a developer's first app is, the less likely the developer is to make a major pivot.

Marginal effects with a 95% shaded confidence interval. Logged app one installs key:

2.4=10 installs, 4.6=100 installs, 6.9=1k installs, 9.2=10k installs, 11.5=100k installs,

13.8=1 million installs).

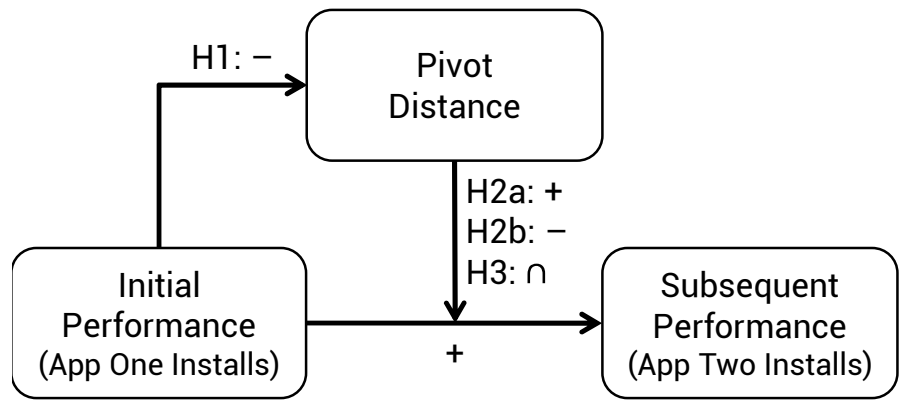


Figure 3.5 Hypothesized relationships.

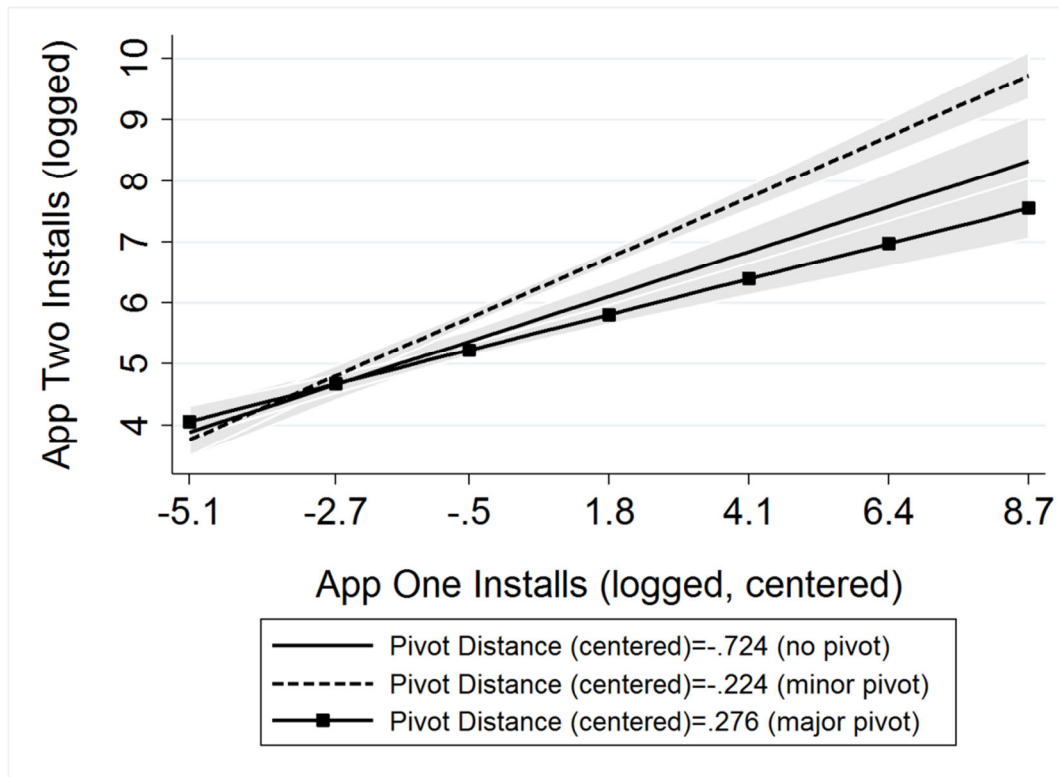


Figure 3.6 App two installs by app one installs and pivot distance. This figure shows the effects of making no pivot (centered pivot distance = $-.724$), a minor pivot (centered pivot distance = $-.224$), or a major pivot (centered pivot distance = $.276$) on logged app two installs, for a given level of logged, centered app one installs. Logged, centered app one installs key: -5.1 (0 installs), -2.7 (10 installs), -0.5 (100 installs), 1.8 (1k installs), 4.1 (10k installs), 6.4 (100k installs), 8.75 (1 million installs).

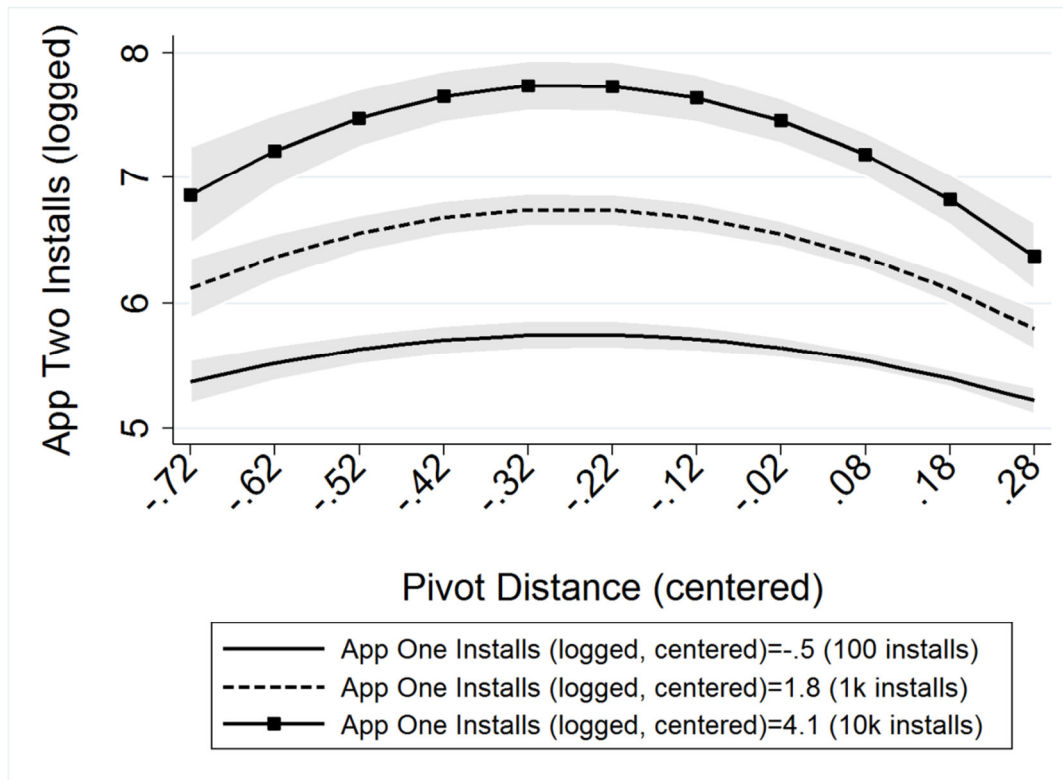


Figure 3.7 App two installs by pivot distance and app one installs.

CHAPTER 4

GETTING LOST IN THE CROWD: OPTIMAL DISTINCTIVENESS STRATEGIC CATEGORIZATION, AND NEW ENTRY ON THE GOOGLE PLAY APP PLATFORM MARKET

Introduction

Organizational scholars have long been interested in the inherent tension organizations face in balancing a need to conform to consumer expectations, while at the same time differentiating themselves from their competitors (Deephhouse, 1999; Dimaggio & Powell, 1983; Haveman, 1993; Oliver, 1997). Indeed, a broad range of disciplines has studied the question of whether it is more advantageous for organizations to fit in or stand out, including: strategic management (Deephhouse, 1999; Oliver, 1991), organizational sociology (Goldberg, Srivastava, Manian, Monroe, & Potts, 2016; Hsu & Grodal, 2015), entrepreneurship (Boone, Wezel, & van Witteloostuijn, 2013), and organization theory (Durand & Kremp, 2016; Rao, Monin, & Durand, 2003; Zuckerman, 1999). Much of this work draws implicitly, and often explicitly, from psychological and socio-cognitive perspectives (Brewer, 1991) of individual social identification, which is then aggregated up to the level of the organization to make inferences about organization-level outcomes. More recent work (Zhao, Fisher, Lounsbury, & Miller, 2017) has sought to integrate much of this literature, and calls for greater scholarly attention to the concept

of optimal distinctiveness. Typically, this process is conceptualized as a balancing act, akin to a zero-sum proposition, where greater differentiation inherently means less conformity, and that the point of optimal distinctiveness is therefore an exercise in finding the balance at the midpoint between two countervailing forces. Yet, in line with this recent call, we view the process of achieving optimal distinctiveness to be “multi-faceted and mutually enabling” (Durand & Paoletta, 2013; Zhao, Fisher et al., 2017).

An important challenge that remains in improving our understanding of competitive dynamics related to optimal distinctiveness is the deceptively simple question: to whom or to what do organizations conform, and differentiate from, in order to gain a competitive advantage? While broadly defined market categories serve as useful classification devices (Hsu & Hannan, 2005; Zuckerman, 1999) towards this end, individual market categories are potentially complex and multidimensional competitive spaces (Cattani, Porac, & Thomas, 2017) in their own right. Thus, positioning within a given market category may be as strategically important as positioning across different market categories. For example, organizations may choose to align themselves with the most representative member in a market space (i.e., the category prototype) in order to signal their legitimacy. Alternatively, organizations may choose to align themselves with the most salient member, or a clear market leader (i.e., the category exemplar), as a means of demonstrating that they stand out from the norm (Vergne & Wry, 2014). This challenge of optimal alignment is particularly relevant for *de novo* market entrants who may not have the requisite experience to fully understand the nuances of the conformity/distinctiveness paradox, and may be even more problematic for these new entrants in highly competitive markets such as today’s platform ecosystems (McIntyre &

Srinivasan, 2017; Thomas, Autio, & Gann, 2015). The complexity of these competitive landscapes makes understanding how organizations optimally position themselves at entry a critical question with significant performance implications.

The goal of this paper, then, is to use the theoretical lens of strategic categorization (Pontikes & Kim, 2017) to investigate the degree to which de novo entrants competing in highly competitive, two-sided, platform markets should align themselves with, or differentiate from, either the prototype or the exemplar of a given product market category. Strategic categorization allows organizations to explicitly align themselves (or aspects of organizational design or identity) to an existing categorical schema for the purposes of gaining a competitive advantage within that market category. We believe that strategic categorization serves as a useful tool to understand these entry choices because it can effectively reconcile the inherent agency that organizations leverage in market entry decisions (Kennedy, 2005; Navis & Glynn, 2010; Vergne & Wry, 2014), with the external pressures that market categories can impose (Hsu, Hannan, & Koçak, 2009; Leung & Sharkey, 2013; Negro, Koçak, & Hsu, 2010).

Drawing on this perspective, we argue and find support for the notion that in two-sided platform markets, strategically aligning oneself with the category prototype may not confer the same legitimizing benefits as in more traditional markets, while aligning oneself with the category exemplar leads to higher performance. Further, we argue and find that alignment with the prototype may actually hurt new entrants and mitigate the positive benefits associated with aligning oneself with the category exemplar. The logic underpinning these predictions is two-fold. First, platform ecosystems are highly competitive and crowded market spaces. As a result, entrants that align themselves with

the category prototype, even if done for the purposes of garnering legitimacy, run the risk of immediately being lost in the crowd. Second, two-sided markets are structured such that producers and consumers are more efficiently able to interact with one another, and as a result, processes of endogenous demand may ameliorate the need for external signals of legitimacy. Endogenous demand entails the ability of organizations to “influence consumer interest in niches through the products that they offer” (Barroso, Giarratana, Reis, & Sorenson, 2016, p. 566), ultimately shaping the development and competitive dynamics of product market categories from within. This emphasis on the demand-side factors that shape competitive advantage is an important factor in understanding how new entrants can compete in highly competitive market spaces and offers an alternative to the supply-side perspective that focus on organization-centric factors, such as dynamic capabilities (Eisenhardt & Martin, 2000; Teece, Pisano, & Shuen, 1997).

We test our hypotheses in the Google Play app platform market. Leveraging a unique dataset of over 107,000 apps from over 82,000 new app developers, we utilize natural language processing of the apps’ text descriptions to identify similarity scores for a focal app, relative to both a category prototype and category exemplar within each of Google Play’s 41 app categories. The results suggest that developers can utilize strategic categorization to position themselves within a highly competitive platform market in order to gain a tangible competitive advantage.

Empirical Context

Platform ecosystems

A growing body of literature has noted the importance of platform ecosystems to today's economy (McIntyre & Srinivasan, 2017; Thomas et al., 2015). Examples of platforms include: internet search engines, Amazon, Netflix, Uber, Airbnb, video game consoles, YouTube, eBay, iTunes, and the Google Play app store. Platforms are intermediaries that facilitate transactions between consumers and producers² in a two-sided business model (Cennamo & Santalo, 2013; McIntyre & Srinivasan, 2017; Zhu & Iansiti, 2012). Consumers use platforms to search for and acquire products and services developed by producers. Producers use platforms to gain immediate access to large numbers of consumers who may be interested in acquiring these products and services.

Platforms benefit from indirect network effects, becoming more valuable as the number of both consumers and producers increases (Cennamo & Santalo, 2013; McIntyre & Srinivasan, 2017; Thomas et al., 2015; Zhu & Iansiti, 2012). In order to foster the development of indirect network effects, many platforms adopt open architectures which minimize entry barriers and encourage large numbers of producers to offer their products and services as a means of attracting consumers to the platform (Thomas et al., 2015). As a result, competition can be particularly intense on successful platforms with a large number of producers competing for the attention of millions (or even billions) of consumers. Indeed, a key benefit for de novo producers entering a successful platform market is that they are immediately exposed to a large number of consumers without having to develop the requisite scope and scale economies that traditional markets require

² In the literature on platform markets, the term “complementor” is often used as the counterpart to consumers. Here we use the term “producer” as a substitute for the term “complementor.”

for this same level of exposure. However, these same de novo entrants simultaneously face the real possibility of immediately becoming “lost in a crowd” of other producers who also operate on the platform. Thus, strategic positioning at entry can be critically important to a de novo producer’s survival prospects in platform markets.

Google Play app store platform

The empirical context for this study is the Google Play mobile application store (<https://play.google.com/store/apps>) for phones and tablets running the Android operating system. Google Play generated an estimated \$17 billion in revenues in 2016 and this number is projected to reach \$42 billion by 2021.³ In 2016, this platform had over 1 billion active monthly consumers,⁴ 700,000 producers (mobile application development organizations),⁵ and 2 million apps.⁶

Many Google Play consumers discover apps through an organic search process.⁷ For example, a consumer looking for a task management app might enter the text “task manager” into Google Play’s search bar. Google Play then executes a search algorithm—which draws on the developer-provided text description for each app⁸—and presents the consumer with a list of apps matching the search criterion. Obtaining a high rank order in this list of search results can help an app receive more consumer attention and generate more installs. Alternatively, a consumer might browse through Google Play’s lists of top apps, click on a popular app, and see a list of similar apps. Building on the same logic as

³ App Annie Market Forecast 2016—2021

⁴ <https://mashable.com/2015/09/29/google-play-1-billion-users/#sS85m8FZsPqq>

⁵ There were 707,831 unique app development organizations in our data set

⁶ <https://www.statista.com/statistics/266210/number-of-available-applications-in-the-google-play-store/>

⁷ <https://www.tune.com/blog/app-store-optimization-win-google-play-app-store-search/>

⁸ <https://support.google.com/googleplay/android-developer/answer/4448378?hl=en>

above, obtaining a high rank order in the list of apps similar to a highly popular app is another way in which producers can receive more consumer attention and generate more installs. Thus, one way in which Google Play app producers can strategically position themselves to receive more attention and generate more installs is through the crafting of an app's text description.

By collecting over 22 million app-month observations between February 2015 and August 2016, we are able to identify 107,106 initial app publications by 82,149 de novo app producers and measure the degree to which these apps are aligned with both prototypical and exemplar apps within Google Play's 41 product market categories. These measures are constructed using natural language processing techniques applied to the text descriptions of all apps in the full dataset. Through these descriptions, producers are able to directly communicate to consumers the features or characteristics that they consider most important, and in the process, position themselves within a given product market category vis-à-vis their direct competitors. Performance outcomes are measured based on the number of times each app was both installed and reviewed by users.

Theory and Hypotheses

Optimal distinctiveness and positioning during market entry

Under certain conditions, the process of achieving optimal distinctiveness can be thought of as a two-stage process: in order to succeed, an organization must first make it into a consumer's consideration set (i.e., be considered a legitimate option), and second, distinguish itself from the others in that set in order to ultimately gain the favor of consumers (Zuckerman, 1999). In other words, an organization should conform just

enough to gain legitimacy, and then differentiate to gain attention (Deephouse, 1999). Organizations (and their product offerings) are able to conform by adhering to identity-based codes or labels attached to market categories (Hannan, Pólos, & Carroll, 2007; Hsu & Hannan, 2005), which communicate information to audience members and consumers, reducing uncertainty and ultimately impacting appeal. Yet, an important step in this process that remains less clear is the optimal way an organization differentiates itself within the consideration set (Rindova & Petkova, 2007), and what it uses as the benchmark or anchor from which it differentiates.

Two perspectives have emerged to help explain how organizations might position themselves within a product market category and how audience members make sense of and interpret different categorical paradigms—prototype and exemplar based models (Durand & Paoletta, 2013; Vergne & Wry, 2014). The prototype model builds on early work in cognitive psychology (Rosch & Lloyd, 1978; Rosch & Mervis, 1975) that sought to interpret categorical distinctions through a process of grouping attributes or features of a given category. These groupings help to explain how “internal structure arises” (Rosch & Mervis, 1975, p. 574), and serve as judgment devices for individuals to make attributions about other actors. Thus, those features that are deemed to be the most central or representative in the mind of the audience emerge as the prototype for a given category (Hannan et al., 2007; Vergne & Wry, 2014). Moreover, these enduring prototypes generate external codes or schemas (Hsu, 2006a, 2006b) that organizations ostensibly benefit from adopting because they reduce confusion among consumers about an organization’s place in the market, and whether they belong there or not.

In contrast, the exemplar model builds on self-categorization which offers a

perspective on how labeling practices inform category dimensionality, and subsequent organization positioning within that category. Self-categorization is driven by a shared understanding among actors of how they fit together and what the salient attributes that define their place within a category or market space are (Vergne & Wry, 2014). A great deal of emphasis is placed on an actor's ability to create or construct their own identity, which bolsters not only the emergence of a shared understanding (Kennedy & Fiss, 2013), but also their place within it. These shared understandings are legitimated through dynamic actions such as storytelling (Wry, Lounsbury, & Glynn, 2011), cultural entrepreneurship (Lounsbury & Glynn, 2001), and linguistic frames (Navis & Glynn, 2010). One example of how these manifest is through the emergence of exemplars as accepted judgment devices (Cohen & Basu, 1987; Dekker, 2016). Exemplars can be understood as those offerings that stand out as particularly salient or exceptional representations of a category. Often, they can be understood as the most well-known, or highest performing members of a group. Exemplars, then, can serve as reference point to de novo entrants who aspire to achieve the same levels of success.

A key decision a new organization faces in gaining a competitive advantage is that of positioning at the time of market entry. De novo entrants can position themselves within a product category across a number of different dimensions which can have long lasting consequences (i.e., imprinting effects) even if they reposition themselves later on (Stinchcombe, 1965). These processes, and their consequences, may be strategically manageable in certain environments, such as in the nascent stages of an industry or market (Anthony, Nelson, & Tripsas, 2016; Moeen, 2017; Zhao, Ishihara, Jennings, & Lounsbury, 2017) because a shared understanding of what the product category

represents has yet to fully emerge (Kahl & Grodal, 2016; Kennedy & Fiss, 2013). Moreover, organizations may also be able to strategically time their entry into a market in order to take full advantage of favorable environmental or market conditions (Lieberman & Montgomery, 1988; Suarez & Lanzolla, 2007). Nevertheless, positioning at time of entry is likely to have a disproportionate impact on organization or product performance over time, particularly in established, highly competitive markets. This is, in part, because de novo organizations which enter highly competitive or crowded market spaces likely do not have the time or resources to “learn as they go.”

A number of factors have been found to impact the relative number and success of new market entrants. For example, market level characteristics such as spatial heterogeneity (i.e., the density and intensity of the competitive environment) and temporal factors have been shown to impact the rate of market entry (Boone et al., 2013; Cattani, Pennings, & Wezel, 2003). Additionally, the level of contrast (i.e., how “fuzzy” a category’s boundaries are) can also influence market entry (Carnabuci, Operti, & Kovács, 2015). Different imitation strategies can also drive relative success of new market entrants (Ethiraj & Zhu, 2008; Posen & Levinthal, 2012), as well as whether an organization enters a market as a de novo (entrepreneurial start up) or a de alio (lateral entrant from another industry) organization (Carroll, Bigelow, Seidel, & Tsai, 1996; Khessina & Carroll, 2008).

Optimal distinctiveness and endogenous demand

We suggest that analyzing competitive positioning at the time of market entry within the context of optimal distinctiveness can serve as a valuable lens to extend this

research. Recent work has argued that there is not one single convergence point for which organizations can attempt to achieve strategic balance within a market category (Zhao, Fisher, et al., 2017). Thus, while singular organizational attributes, or specific environmental conditions, are important in understanding organization performance and heterogeneity, it is critical to understand the multi-dimensionality of a given market and how organizations are positioned relative to these multiple competitive reference points. Understanding competitive positioning through an optimal distinctiveness lens places increased emphasis on demand-side factors (such as how consumers and audience members perceive organizations), as opposed to supply-side factors (such as efficiencies that organizations gain through scope and scale economies) when attempting to explain competitive advantage. In other words, we suggest that markets across an increasing number of industries are being shaped by endogenous demand (Barroso et al., 2016), or an iterative process between producer organizations and consumers that shapes market dynamics and organization performance (Rosa, Porac, Runser-Spanjol, & Saxon, 1999).

Processes of endogenous demand are particularly salient in markets where product offerings differ on dimensions that are difficult to compare directly or systematically (Barroso et al., 2016), such as cultural products (i.e., music, art, video games, etc...) in rapidly innovating markets. Structural alignment theory (Gentner & Markman, 1994; Markman & Gentner, 1993) suggests that the reason for this is that these types of offerings predominantly differ on nonalignable attributes, which can be defined as attributes that cannot be easily compared between offerings. In contrast, alignable attributes can be easily compared between offerings, for example when comparing the memory, processing speed, or size of different optical disk drives for computers.

Therefore, in markets where nonalignable product attributes are prevalent, organizations should benefit from the ability to directly engage the consumer and increase interest in their position in a market space (based on the attributes they possess).

Two-sided platform markets, then, are particularly well suited for these processes of endogenous demand because they are structured to facilitate producer-consumer interaction, and also because they are often based on offerings which possess nonalignable attributes. For example, on the Google Play app platform, individual games within the game category clearly possess some alignable attributes. Different games can easily be compared by app size (in megabytes when installed on your device), which version of the Android operating system they work on, whether they are free vs. paid, and if they offer in-app purchases. However, the popularity of different games is likely driven more by the nonalignable features, such as the functionality or specific features of the game, which may vary dramatically between games. For example, the attributes that make the military game ‘Call of Duty’ popular compared to those that make ‘Candy Crush’ popular are very different. Desirable attributes for Call of Duty might be a multiplayer online functionality, incorporating the latest weaponry and drone technology, or how realistic the violence appears in terms of the graphics. For Candy Crush, the relevant attributes might be the ability to collect sugar drops or ‘spin the daily booster wheel for a delicious prize’ (for example, a lollipop hammer or bubblegum troll).

In these instances, endogenous demand offers producers the ability to directly engage consumers and highlight the relevant attributes that are relevant to each app. By doing this, producers are able to reduce possible confusion by consumers and help them to make sense of these nonalignable features within a product market category. In this

context, the app descriptions on the Google Play offer provide one important avenue to accomplish this. It also allows producers to position apps upon entry relative to competitors, and align themselves with a prototypical game app, an exemplar game app, both, or neither. Importantly, because of the sheer size of platform markets such as Google Play, the highly competitive and crowded nature of each app category makes positioning at entry particularly important.

Strategic categorization

This study focuses on the positioning choices that de novo producer entrants face within a product category on the Google Play App Store platform. Importantly, it builds on the assumption that there is more than one anchor that organizations can use to position themselves in a competitive environment (Durand & Kremp, 2016). We identify two possible judgment devices, prototypical members and exemplar members of a given market category, that are both rooted in the categories and organization theory literature, yet are rarely considered in conjunction with one another (Durand & Paoletta, 2013; Vergne & Wry, 2014). Moreover, there is little empirical evidence demonstrating that both of these judgment devices can operate concomitantly to aid market position and entry choices by de novo organizations. This section addresses this theoretical and empirical lacuna by suggesting that de novo entrants can use *both* prototype and exemplar perspectives to identify the optimal strategic positioning within a given product category space. In order to accomplish this, we build the theoretical concept of strategic categorization (Pontikes & Kim, 2017).

Organizations typically make strategic choices in an attempt to gain a sustained

competitive advantage against rivals. Often, these choices manifest as internal structural characteristics (i.e., vertical integration, diversification, or the development of key resources and capabilities) that allow organizations to capture valuable efficiencies based on scope and scale economies (Barney, 1991). Increasingly, however, competitive rivalry is being shaped by endogenous market dynamics that arise when producers and consumers engage in an iterative process of categorization and competitive sensemaking (Cattani et al., 2017; Rosa et al., 1999). One specific way that organizations can engage in this process, and directly influence consumer perceptions of their products and actions (Barroso et al., 2016), is by strategic categorization. We define strategic categorization as explicitly aligning or linking an organization (or aspects of organizational design or identity) to an existing categorical schema for the purpose of gaining a competitive advantage over competitors within that category. Pontikes and Kim identify two fundamental benefits of strategic categorization for organizations: “to communicate information and to position themselves favorably with respect to competitors” (2017, p. 73).

Strategic categorization offers a key advantage in that it allows organizations to shape the narrative of their positioning in a competitive landscape. Typically, these narratives are left to third-party market intermediaries who take the form of industry experts or analysts (Zuckerman, 1999), the media (Kennedy, 2008), or professional critics (Rao et al., 2003). While third-party participation often aids organizations by making sense of categorical distinctions and helping “to penetrate opaque buyer-supplier interfaces” (Cattani et al., 2017, p. 78), these third-parties can also use categorical membership as a sanctioning mechanism for organizations that deviate from accepted

categorical codes or schemas (Zuckerman, 1999). Strategic categorization can allow organizations to bypass third-party actors that serve as sanctioning mechanisms, or emphasize other third-party actors that benefit them, ultimately using categorization as a means to intentionally achieve a specific goal or objective (Pontikes & Kim, 2017; Vergne & Wry, 2014). This can be particularly valuable in market categories that exhibit high levels of diversity in terms of offerings, or heterogeneity in consumer preferences. The implication is that organizations can actively distinguish between different consumers as much within market categories as across them. For example, in the beer industry, brewers of mass produced beer (i.e., Budweiser and Miller) often adopt different strategies depending on their target audience. Specifically, they will categorize or align themselves with the prototypical American beer style (a pale lager) when trying to reach mainstream beer consumers, and alternatively align themselves with other types of beer (Belgian witbier or German weiss beer) when attempting to court craft beer consumers, who have different preferences from consumers who prefer mass-produced beers (Barlow, Verhaal, & Hoskins, 2016; Carroll & Swaminathan, 2000). In the latter case, mass-producers strategically categorize their offerings as being artisanal or handcrafted and typically hide the fact that their offerings are mass-produced and owned by giant international beverage conglomerates (Howard, 2017).

Up to this point, we have argued that organizations can use strategic categorization to both directly communicate information to audience members and effectively position themselves within a product category. Yet, a key question that remains is how to go about accomplishing this. In other words, what are the actual tools that organizations have at their disposal to shape and influence market demand for their

goods or services? We identify one potential practice that organizations can leverage – drawing on an existing categorical nomenclature (Cattani et al., 2017). Categorical nomenclatures serve as a semantic tool for “labeling, codifying, and diffusing category relevant market conversations” (Cattani et al., 2017, p. 78). Moreover, categorical nomenclatures can aid in transferring the two key benefits of strategic categorization: communicating information and positioning an organization favorably vis-à-vis its rivals. Over time, these nomenclatures also help to clarify category schemas (Hannan et al., 2007) which may not yet be fully developed (in the case of nascent categories or industries), or schemas that may mislead or distort consumers as to the actual characteristics of a given organization (Hsu & Grodal, 2015). Categorical nomenclatures can manifest through direct communication with consumers, advertising, or product descriptions – in effect, anything that the organization uses to communicate information or strategically position itself within the category.

Strategic categorization and similarity to an exemplar

We suggest that in platform-based markets, strategic categorization is a particularly useful tool for producers to directly engage and influence consumers and audience members. Producers can accomplish this by positioning themselves relative to category prototypes and exemplars. We argue that positioning based on conformity to a category exemplar will ultimately be beneficial for de novo producers. The logic underpinning this is that conformity to the exemplar is conducive to a goal-based approach to category positioning that is driven by positive rewards as opposed to penalty avoidance (Durand & Paoletta, 2013; Pontikes & Kim, 2017). Exemplars stand out, and

while they may run the risk of being questioned in terms of their legitimacy, the benefit from their ability to stand out from the crowd is particularly important in crowded or competitive environments.

Extending this logic to markets (such as platform ecosystems) where producers are immediately exposed to large number of potential consumers, we believe that producers will be more successful by aligning with exemplars at the time of entry because they are more likely to gain attention from and be found by consumers looking at the exemplar products. In other words, processes of endogenous demand in two-sided markets, where producers and consumers have more direct control over shaping market demand themselves, reduces the need for legitimacy from external actors while simultaneously increasing the attention the producer can gain from the audience. This allows producers to focus their positioning choices on goal and reward-based strategies over penalty avoidance strategies. As a result, the categorical nomenclature that they use to strategically categorize themselves should align them more heavily with category exemplars in an attempt to stand out from the crowd and gain the attention of the audience.⁹

For example, in our empirical context, the Google Play app market, producers have significant freedom to strategically categorize themselves and create a categorical narrative (or nomenclature) that can endogenously influence consumer demand.¹⁰ They

⁹ This does not mean that market intermediaries do not still play an important, and sometimes deciding, role in market outcomes. Yet, endogenous demand and strategic categorization in two-sided markets should allow them to reap the benefits of market intermediaries that serve as facilitators in the process of endogenous demand, without being penalized by those that play a sanctioning role (relative to more traditional markets).

¹⁰ Compared to Apple's App Store, Google Play employs a much less rigorous prepublication review and approval process. As long as a proposed app does not contain malware or offensive material and does not infringe on copyrights, the app is likely to be approved as a member of whatever category the producer has

also face a highly crowded and heterogeneous market space. During the time of this study Google Play’s “Communication” category had over 35,000 unique apps, and included an incredibly diverse set of web browser, social media, direct messaging, email, video chat, and caller ID apps. To illustrate the benefits of exemplar conformity, consider a de novo app producer entering Google Play’s Communication category with a new web browser app. This category has exemplar web browser apps with hundreds of millions of downloads such as Firefox. The nomenclature of these exemplars includes words that are not part of the category prototype’s nomenclature such as: *bookmark*, *browse*, *engine*, *fast*, *incognito*, *intuitive*, *page*, *privacy*, and *web*. We argue that a de novo app producer that crafts the text description of its web browser app in a way that aligns it closely with the exemplar nomenclature will be well-positioned to capture the attention of consumers and potentially generate a high level of installs for a number of reasons. This is because the similarity of the new app’s text description to the exemplar nomenclature increases the likelihood that the new app will appear in search results when consumers search for web browsers using Google Play’s search bar. Moreover, even if consumers first click on one of the exemplar apps, the new app’s similarity to the exemplar increases the likelihood that it will show up in Google’s list of similar apps displayed within the exemplar app’s product details screen. In either case, the new app’s similarity to one or more exemplars increases the likelihood that it will be seen by and subsequently downloaded by consumers.

Therefore, we argue that in crowded two-sided platform markets, alignment with a category exemplar enables producers to stand out from the

chosen in a matter of hours (<https://android-developers.googleblog.com/2015/03/creating-better-user-experiences-on.html>).

crowd and achieve higher performance. This leads to the following hypothesis:

Hypothesis 1. *The more an app conforms to a market category exemplar at the time of entry, the greater the performance of that app.*

Strategic categorization and similarity to the prototype

Given the argument that there are multiple reference points organizations can use to position themselves at entry, and our suggestion that conformity to the exemplar should drive attention and increased performance in highly crowded and competitive market categories, a logical conclusion is that de novo entrants can simply focus their attention on strategic categorization around the exemplar and ignore its positioning vis-à-vis the category prototype. However, we believe these two alternatives to be more interdependent than previously recognized in the literature, and that achieving a truly optimal strategic position within a given product category requires accounting for both positions in tandem. This creates a more complex market space, but also more accurately reflects the competitive dynamics that organizations actually face. Indeed, organizations often engage in multiple strategies simultaneously, and also attempt to position themselves in different parts of the market, or toward different sets of consumers at the same time. For example, it is becoming increasingly popular for high-end chefs to open up fast-casual restaurants, in an attempt to leverage their reputation and reach a broader audience, without compromising their high-status credentials.¹¹ This can occur when organizations reinterpret existing category labels (Negro, Hannan, & Rao, 2011), causing rivals to make differing claims about the same labels, or audience members interpreting

¹¹ “Why Fine Dining Chefs Are Getting into the Chain Game”, by Erin DeJesus.
<https://www.eater.com/2014/10/6/6896297/why-fine-dining-chefs-are-launching-fast-casual-concepts>

similar claims differently.

The implication is that de novo entrants can potentially position themselves near a prototype and an exemplar simultaneously. Of course, this assumes that both of these reference points already exist within the market category. For example, in nascent markets a true category prototype may be too difficult to identify because the structures, codes, and categorical nomenclature have not had sufficient time to develop (Navis & Glynn, 2010; Zhao, Ishihara, et al., 2017). However, a potential problem with this strategy is that strategic categorization is not an infinite resource. Consumers can become overloaded with information, and this may negatively impact appeal. Moreover, organizations may have limits to the amount of communication they are afforded with consumers. For example, on platform-based markets (such as Google Play) producers may be limited by the amount of space to write their product descriptions. Finally, in line with the well-known penalty for category spanning (Hsu, 2006a; Hsu et al., 2009; Leung & Sharkey, 2013), being positioned as both a prototype and an exemplar within the same category can sow confusion about the true identity of a producer if consumers in that category are more or less homogenous. Nevertheless, in highly competitive and heterogeneous market category spaces, organizations can ostensibly position themselves differently in order to engage different customers within the same category.

In addition, successful strategic categorization is not necessarily only a function of alignment within a certain market category. Indeed, organizations can strategically avoid certain categorical nomenclature in order to intentionally position themselves away from a category prototype and/or exemplar. For example, strategic categorization can entail conformity to the exemplar and

nonconformity to the prototype. The potential benefit of this is that it creates clarity in the information being communicated through strategic categorization. It also creates greater degrees of contrast between organizations. Past research has shown that high levels of contrast can benefit organizations (Kovács & Hannan, 2010) and that new entrants fare better in high contrast environments (Carnabuci et al., 2015).

To illustrate the drawbacks of prototype conformity, consider a *de novo* producer entering Google Play's Communication category with an app for delivering personalized communications, news, and notifications to employees of large corporations. Assuming there are no exemplar, highly successful, personalized corporate communication apps in Google Play's Communication category, how should this app strategically categorize itself upon entry in this competitive market category? The prototypical nomenclature for this category includes words such as: *message*, *notify*, *connect*, *contact*, *chat*, *inform*, and *share* – all of which are words this producer might use to describe a personalized corporate communication app and suggest that the app is a legitimate member of the Communication app category. Yet, these words also apply to a whole host of other Communication apps, and if consumers were to search based on these words, the app could quickly run the risk of being completely overwhelmed by other offerings, effectively being lost in the crowd. While using some of these terms in the personalized corporate communication app's text description may be inevitable, the more heavily they are used, the more the Google Play algorithm will group them in the search results with thousands of other apps that offer these

features as well. In the event that this app does not reach the first page of a consumer's search results on the platform, the producer is likely to be at a severe disadvantage. In this instance, then, the need to stand out from the crowd should outweigh the need to signal legitimacy by explicitly stating that an app is a true member of the Communication app category.

Particularly for idiosyncratic and unique apps (such as the personalized corporate communications app), the need to stand out from the crowd is acute. One of the key benefits of platform markets is that they facilitate outreach to, and communication with, an extremely scattered and diffuse target market. In more traditional product markets, the producer of this app would struggle to generate the marketing budget or economies of scale to reach these consumers. But through the direct interaction inherent in the process of endogenous demand on two-sided markets, these unique products are potentially able to reach consumers and thrive. The key, then, becomes strategically categorizing an app in a way that reaches this broad and diffuse consumer set without getting lost in the crowd in the process.

Therefore, we argue that in crowded two-sided platform markets, alignment with the category prototype will not produce the performance benefits related to legitimacy and will instead lead to lower performance due to getting lost in the crowd. This leads to the following hypothesis:

Hypothesis 2. The more an app conforms to its category prototype at the time of entry, the lower the performance of that app.

Up to this point we have argued that in competitive two-sided markets

strategic alignment with the category exemplar will lead to higher performance because it helps new entrants stand out in a crowded market space. Furthermore, because of the nature of these markets and the ability of producers to directly engage consumers through processes of endogenous demand, the need to conform to a category prototype as a means of garnering legitimacy is less important. In fact, we suggest that new entrants will perform significantly worse the closer they align themselves to these prototypes. Indeed, so strong is the need to stand out from the crowd that we also argue that alignment with the category prototype can actually negate other successful positioning strategies taken by de novo entrants. Market categories can be complex multidimensional spaces, and organizations may pursue more than one strategy in order to reach different sets of consumers within the same market category. The example above of mass production breweries attempting to court both mainstream beer consumers and craft beer consumers simultaneously is just one example. Yet, it is difficult to completely disentangle or separate these actions from one another. As a result, new entrants who position themselves near prototypical offerings in order to fit in may inadvertently impair their ability to be perceived as unique and stand out from competitors.

For example, a de novo producer entering Google Play's Communication category with a video calling app would likely be similar not only to an exemplar with billions of downloads (such as Facebook Messenger), but also to the category's prototype. The text description of the new video call app would likely include nomenclature such as: *call*, *video*, *chat*, *contact*, *message*, *send*, and

connect. These words are all part of the nomenclature of exemplar video call apps—but they are also part of the category’s prototypical nomenclature used by many thousands of apps. Thus, even if the new app were to appear in Google Play’s search ranking list (or the list of apps related to an exemplar), it stands the risk of being lost in the crowd and ending up so far down the list that it is unlikely to be discovered by consumers. As shown in this example, similarity to a category’s prototype can negate the benefits of similarity to a category exemplar in highly competitive platform markets. The key, then, would be for this producer to invoke a categorical nomenclature that strategically aligns it with the exemplar, without simultaneously invoking a prototypical nomenclature.

Ultimately, we argue that the need to stand out in highly crowded platform market categories is so important that the penalty for alignment with the prototype will negate the strategic benefits of alignment with an exemplar. This leads to our final hypothesis:

Hypothesis 3. The greater an app’s conformity to its category prototype at the time of entry, the smaller the performance benefit of that app’s conformity to a category exemplar.

Methods

Data

Google Play publicly provides rich data for each app, including the number of downloads, the number of reviews received, a category classification, a history of version changes, and – importantly for this study – a complete text description of each app

written by the developer. These descriptions represent a key tool for developers to communicate directly with potential consumers and, in our study, serve as a means to identify and measure variation in strategic categorization across developers. Google advises developers that it is imperative to use a strong description to help their app get found in the market.¹²

To create the sample, we collected data on over 1 million apps on a monthly basis between February 2015 and August 2016. In this setting, thousands of new apps are published every month as developers attempt to generate economic value in a single marketplace. This makes it relatively easy to identify a sample of nascent app development organizations entering the market for the first time and track the performance of the apps published by these developers over time. To test this study's hypotheses, we restrict the sample to include only developers who published their first app between March 2015 and July 2016. We exclude any developers who publish more than 10 apps during our collection period, since those developers are more likely to be larger companies or even contract development organizations, which we are not theorizing about, and may have very different market strategies compared to new developers.

Importantly, we only examine the first set of apps each developer places on the market. For example, if a developer builds and places three apps on the market in $t=1$ (the first month of observation), and then introduces two more apps on the market at $t=2$, we only examine the developer's first three apps. We do this because the developer could have learned from their experiences with the first set of apps that they apply to this

¹² <http://www.adweek.com/digital/google-discloses-how-search-for-google-play-works-for-the-first-time-12-percent-of-dau-search-for-apps-daily/>

second set of apps, which introduces organizational learning processes, which may confound the interpretations of our results. We do include developer-level controls to account for these new apps, but this paper specifically theorizes about how to optimally place products upon initial entry of developers, leaving questions of learning from these choices for other studies.

We also exclude developers that did not publish apps with an English text description and developers with data collection gaps. Finally, because we include a lagged review score measure to control for app quality, any apps with either no review score in the prior month or that were only on the market for only 1 month are dropped from the final analysis (although our results hold with these apps included by unlagging the measure). Our final sample consists of 470,728 app-month observations, with 107,106 unique apps, and 82,149 unique developers.

Our hypotheses argue that app developers achieve better performance for their initial apps at high levels of similarity to a category exemplar, and low levels of similarity to the category prototype. Initial analyses of the data reveal that most developers do not appear to follow either of these two strategies. Figure 4.1 shows a scatterplot of the similarity scores for each app in the dataset. This figure clearly shows most apps are clustered in the area where they are low in similarity to both prototypes and exemplars. This suggests that, if our hypotheses are correct, most app developers are not optimally positioning their apps for competitive advantage and high levels of performance.

Measures

Dependent variable. We use *Review Count (ln)*, the logged count of reviews for each app-month observation as our primary dependent variable. The logged count of downloads would also be a logical measure of app performance. However, the downloads measure obtained from Google Play is ordered and categorical (e.g., 0, 1-5, 5-10, 10-50, etc.). We therefore favor the use of the continuous measure of logged count of reviews, although our results hold when using either measure of performance. This consistency in results is not surprising since the review count and installs measures are highly correlated (0.80). Only users who have downloaded an app are able to give it a review score in Google Play. We chose a logged measure because the distribution of review counts on the Google Play app store is highly skewed, with the median number of reviews (9) well less than the average (588.7). Further, over 90% of the apps in our sample have less than 237 reviews (while the maximum number of reviews is 5,662,447). We add 0.01 to all review counts before logging to account for apps that have not yet received a review.

Independent variables. We draw on the text descriptions of the apps in our sample to produce this study's two key explanatory variables. When publishing an app on the Google Play platform, developers must write a text description of their product, offering an opportunity for the developers to highlight what they view as the key characteristics or features of their app. In our sample, the mean cleansed description length is 486.48 characters. We use natural language processing methodologies to identify the primary language for each app's text description (ensuring that only English apps are included in the sample), remove stop words (e.g., 'the,' 'your,' 'for,' etc.), and stem words to their root form (e.g., 'fish' would be the stem for 'fishing,' 'fisher,' and

‘fished’) before producing our explanatory measures. It is important to note that our two explanatory variables measure the similarity of each focal app to its category prototype and category exemplars the month prior to publishing the new app. In other words, although our regression sample only includes de novo app developers publishing their first app, we create these explanatory measures by comparing the text description of each new focal app to *all* of extant apps that were available for download in its category by drawing on our larger dataset with over 22 million app-month observations.

First, we calculate *Prototype Similarity*, which measures how similar the focal app in our sample is compared to the representative, or prototypical app in the focal app’s category. To accomplish this, we identify the 50 most commonly used words contained in the descriptions of *all* of the apps (not just the apps within our subsample of de novo developers) in each of Google Play’s 41 app categories on a monthly basis. This measure is based on the top 50 words used in the focal app’s category the month before it was first published. By looking at the prior month, we are able to capture the competitive environment at entry. We calculate the prototype similarity measure by dividing the count of words in a focal app’s text description that are also words from the category’s top 50 words by the total number of words in the focal app’s text description. Thus, a score of 0.0 would indicate that the focal app does not use any of its category’s top 50 words and differs significantly from that category’s prototypical or most representative app. A score of 1.0 would indicate that an app only uses words from its category’s top 50 words list in its text description and is highly similar to the prototypical app. In our sample, the mean prototype similarity score is 0.22. Importantly, the prototype of each category is not necessarily an actual app in the category. Rather, it is a measure of fit

with the characteristics or features that most commonly define that category space. For example, for apps in the Health and Fitness category, some of the most commonly used words in the descriptions include: track, schedule, calculate, program, diet, calorie, and store. Thus, a prototypical app in this category will likely offer the ability to track your progress, create a workout schedule, track calorie intake, and store your workout results. A new entrant can align themselves with this prototype by communicating or highlighting these features in their own description.

The second explanatory variable, *Exemplar Similarity*, measures how similar the description of the focal app is to its nearest neighbor among its category's list of the top 100 most installed apps (the exemplar apps) in the month prior to the app being introduced. Again, this measure is created by comparing the focal app's text description to *all* extant apps that were available in the focal app's Google Play category the month before the focal app was first published. This ensures that we are capturing the competitive environment as the de novo app developer would have seen it when positioning their new app on the market. To calculate the measure, we follow prior literature (Hoberg & Phillips, 2010), and calculate the cosine of the angle between two vectors to determine how similar the two vectors are. In this case, we first create a unique vector for each app in our sample. These vectors represent a list of all the words used in a particular app's cleansed text description (which includes only the stemmed words with stop words removed for apps with English text descriptions). We also create a unique vector for each of the top-100 apps in each of Google Play's 41 categories. We then calculate the dot product between the focal app's vector (A) and the vector for each of the top-100 exemplar apps (B) per Formula 1:

$$\frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (1)$$

Finally, we identify the focal app's nearest top-100 neighbor (single highest cosine similarity score) from this list of 100 scores and use this as our measure of exemplar similarity. For example, an exemplar similarity score of 0.0 would indicate that the focal app does not contain any of the same words as any of the top-100 apps. An exemplar similarity score of 1.0 would indicate that the focal app has a text description that is identical to at least one of its category's top-100 apps. In our sample, the mean exemplar similarity score is 0.33.

Control variables. We include a number of control variables to account for potential omitted variable bias and to control for other factors that may impact an app's performance on the market. We include several variables at the app level. First, we include the number of category name words used in the app's description (i.e., an app from the Books and Reference category that used the stemmed words "book" and "refer" in its description would contain a value of 2 for this variable). Second, we include the order of the app's entry on the market. This variable is measured by examining the 'last updated date' for the app. Since these apps are all new on the market in the month we began our data collection, this variable is a proxy for the date when the app was uploaded to the marketplace. We also include the age of the app, which is the number of days between each wave and the first 'last updated' date for each app. Also included is a binary indicator to identify if the app is free (versus a paid app), and another to show if the app offers in-app purchases. Both of these variables are indicators that the app developer is trying to create value (although in-app advertising is also an important and

growing source of revenue). We also control for the total length of each app's description (in characters), and the app size (in megabytes). We also include a binary variable that indicates if the developer ever changed their description in the future. About 65% of the apps in our sample never changed descriptions. However it is important to control for future changes in our models. Finally, we also include a control for the review score for each app. To calculate this variable, we take the average of all reviews (between 1 to 5 stars) for each app in a given month. We lag this variable by 1 month to reduce potential endogeneity.

At the developer level, we first control for the percentage of a developer's apps that use category name words. Second, we control for the number of other categories the developer has apps in for each month. This variable can vary from 1 (no spanning), to 10 (all apps in different categories, capped at 10 because we exclude de novo developers that enter Google Play with more than 10 apps). We also include a binary variable that indicates whether or not the developer entered with two or more apps in their initial entry month.

We also include a number of controls at the category and market levels. These measures are calculated by drawing on our larger dataset and are not restricted to just the subsample of de novo app developers. First, we include the competitive density of each app category, which is the count of the total number of apps in each category in each observation month. Second, we include a measure of category contrast, as this has been shown to impact the performance of category members (Kovács & Hannan, 2010; Negro et al., 2010). To measure this, we first calculate the total number of cleansed words for all apps in a given category, and then determine how many of these words (at the

category level) are in the top 50 category words list. Lower scores on this variable indicate that the category has higher contrast (the apps within the category are more similar). This variable is lagged by 1 month to reduce endogeneity. We also include category-level fixed effects to control for all other factors that do not change within a given category over time. At the market level, we also include month level fixed effects to account for temporal factors.

Analysis technique

Our data consist of repeated measures of app performance over time, so we used panel-data modeling techniques. Standard fixed effects regression models are inappropriate, since our main independent variables do not vary over time (they measure similarity at app entry). Therefore, to test our hypotheses, we utilize time-series generalized estimating equations originally developed by Liang and Zeger (1986), which account for potential autocorrelation in the data and calculate population average results. Our data include apps nested within a developer, and this could lead our errors to be correlated between different apps from the same developer. Therefore, we also follow Cameron, Gelbach and Miller (2011) and utilize cluster-robust standard errors at the developer level, as the developer is the highest level of nesting within our data. We further tested our models using the two-way clustered errors described by Cameron, Gelbach and Miller (2011), but found similar results to the GEE regression models. We also ran standard random effects regression models, with errors clustered at the developer level, as well as cross-sectional regression models keeping only the last wave of data for each app and clustering the errors at the developer level. Finally, we ran a linear mixed-

effect model that allowed the intercept to vary for each developer (random intercept model). Results from all of these tests were consistent with our findings using the GEE models. Since all of our modeling techniques led to similar results, we have chosen to present to GEE models for simplicity. All additional models tested are available from the authors. To test the fit of our GEE models we employ the quasi-likelihood under the independence model criterion command created by Cui (2007). With this method, lower values of the outcome indicate a better model fit. We tested all of our models and found that the model including all of our controls and predictors (including the interaction) is the best fitting model.

Results

Correlations and summary statistics are provided in Table 4.1. When examining the correlations, results show that our two predictor variables (prototype and exemplar similarity) are positively correlated (0.56). The scatterplot pattern in Figure 4.1 also highlights this correlation, with a large number of apps positioned low on both of these similarity measures. However, when only these main effects are included, we see no evidence of multicollinearity (with variance inflation factors below 2). Since we are hypothesizing a multiplicative interaction, which increases the variance inflation factors (to a max of about 10), we mean-center our independent variables and include the interaction of the centered variables in our models. Models using the uncentered variables give substantively the same results as using the centered variables, but the centered variables lead to much lower variance inflation factors (below 2). Therefore, we see no evidence of multicollinearity biasing our results.

Results for the hypothesized effects are shown in Table 4.2. Model 1 introduces the control variables, which act in the expected ways. It is interesting to note that the lagged review score coefficient is negative and significant. One explanation for this is that most apps start with high review scores (likely reviews from friends and family) and tend to drop as more people (who are likely to be more objective) install and review the app. Model 2 introduces the main effects of both similarity scores, while Model 3 tests the interactive effect. For testing H1 and H2, we see in Model 3 that the coefficient for prototype similarity is negative ($b=-0.663, p=0.000$) and that the coefficient for exemplar similarity is positive ($b=0.793, p=0.000$). Figure 4.2 shows the average performance effect results for both similarity measures, holding all other variables constant. The dependent variable for this plot is review count (as opposed to the log of review count) to ease interpretation. As shown, apps positioned closer to the prototype perform worse than those positioned away from the prototype. An app that has a centered prototype similarity score of 0.0 (the mean prototype similarity score) has an average of 15.5 reviews while an app with a centered prototype similarity score of 0.6 has an average of 10.5 reviews. Thus, a 0.6 increase in the prototype similarity score decreases the expected count of reviews by 5, or 32%, all else being equal. In contrast, positioning close to the exemplar leads to higher performance. An app that has a centered exemplar similarity score of 0.0 has an average of 15.5 reviews while an app with a centered exemplar similarity score of 0.6 has an average of 25.0 reviews. Thus, a 0.6 increase in the exemplar similarity score increases the expected count of reviews by 9.5, or 61%. This lends support to both H1 and H2.

Turning to H3, we see that the interaction effect between the two similarity

measures is negative ($b=-1.003$, $p=0.006$) in Model 3. To explore this effect in greater detail, Figure 4.3 plots the performance of an app with all control variables held at their means versus both prototype and exemplar similarity measures (interacted) in 3-dimensional space. As before, the outcome variable is review count to ease interpretation. As shown, the highest levels of performance are at low levels of similarity to the prototype (-0.2) and high levels of similarity to an exemplar (0.6) where an app can reach, on average, 40 reviews. However, the beneficial effect of similarity to the exemplar diminishes considerably across the range of similarity to the prototype. Apps with high exemplar similarity (0.6) and high prototype similarity (0.6) receive, on average, only 10 reviews (a performance decrease of 75%). This is a large effect, since the median number of reviews for apps in our dataset is 9, and the 75th percentile is 43 reviews. In other words, by adopting an optimal positioning strategy, a de novo app developer can improve their expected performance from the median level to the 75th percentile. Put differently, high levels of similarity to the prototype almost completely erases the advantages of alignment with an exemplar. Indeed, the results in Figure 4.2 show that apps that have high centered scores (0.6) for both similarity measures fare worse (10 reviews), on average, than apps with low centered scores (-0.2) for both similarity measures (15 reviews). This highlights the interdependent nature of these two reference points and suggests that it is not sufficient to attempt to identify optimal positioning based on a single reference point within a market category. New entrants can benefit from developing an understanding of the multidimensional and complex nature of the market category they are entering. Overall, these results provide support for H3.

Robustness checks

We ran several additional models to further test our results. First, since our models (and many econometric techniques) predict *average* performance, we sought an empirical test that could predict *superior* performance. On the app store, the distribution of downloads is highly skewed, with only a small number of apps (approximately 4% of our sample) ever generating 100,000 or more downloads. Therefore, we created a binary variable for all apps that reach the 100,000 download level. We then ran a logistic regression model, with robust standard errors clustered at the developer level. We only keep the last month's observation for each app, which would likely be the app's highest level of performance. Table 4.3 shows this model, and the results indicate that our main findings still hold. High exemplar similarity coupled with low prototype similarity leads to the highest chance of reaching 100,000 or more downloads. Figure 4.4 shows the predicted probabilities of reaching this level of performance depending on prototype and exemplar similarity scores. As shown, low levels of similarity to the prototype and high levels of similarity to the exemplar leads to a 20% chance of achieving 100,000 or more downloads. This is a large effect, since a randomly chosen app has only a 4% chance of reaching this level of performance. Moreover, as a focal app that is highly similar to an exemplar increases its similarity to the prototype, it loses essentially all of its increased probability of superior performance. This effect is consistent with the main models predicting average performance. Therefore, being properly aligned relative to both prototype and exemplar category judgement devices not only improves a developer's chances to achieve better than average performance, but also increases a developer's likelihood of achieving superior performance.

As a second robustness check, we run our original tests with an alternative dependent variable: the logged number of downloads. Consistent with our main models, we find that similarity to the prototype leads to lower downloads, that being more similar to the exemplar leads to an increase in downloads, and that there is a strong negative interactive effect. These results are available from the authors.

Finally, because of the increased power associated with a large number of observations, we test to see if our results hold only looking at the first month an app is on the market. This avoids the possibility that a few high performing app, which are in our sample multiple times (across a number of months), are not driving our results. We show this by running a cross-sectional regression model with the first month that each app is on the marketplace. These models include all of our controls from our main regression models (with the exception of lagged review score, as this is the first month each app has been on the market). These results, also available from the authors, show that our results hold. This indicates that being optimally positioned relative to the prototype and exemplar category members has an immediate impact on performance, and coupled with our main models in Table 4.2, suggests that this positive benefit persists over time. The cross-sectional model also holds in the expected directions with the log of downloads as the dependent variable.

Discussion and Conclusion

This paper provides an answer to the deceptively simple question: To whom or to what do organizations conform to, and differentiate from, in order to gain a competitive advantage on platform markets? To answer this question, we draw on the strategic

categorization literature and identify two judgment devices organizations can align with or differentiate themselves from: the category prototype and a category exemplar. Our findings show that these two judgment devices are interdependent and highlight the importance of considering both in tandem when making entry positioning decisions. We argue and find support for the notion that organizations can strategically categorize themselves and endogenously influence demand for their products in two-sided platform ecosystems such as the Google Play app store. In particular, we find that alignment with the category prototype in a platform market may not confer the same legitimizing benefits as in more traditional markets. We also find that aligning with a category exemplar leads to higher performance outcomes for producers but that this effect is fully negated when alignment with the prototype is also high. Thus, this research investigates the multi-dimensionality and interdependence of different strategic positions within a product market category at the time of entry and shows the importance of optimizing relative to multiple judgment devices simultaneously to gain competitive advantage.

This paper adds to several current research streams. First, we make contributions to the literature on optimal distinctiveness (Deephouse, 1999; Zhao, Fisher, et al., 2017) and organizational positioning at market entry (Boone et al., 2013). This research shows that an organization's decision to optimize product positioning at entry is more nuanced than previous literature suggests. Positioning within a market category is not simply a zero-sum game that consists of making tradeoffs between conformity to and differentiation from a single reference point. Instead, there are multiple judgment devices that organizations can think about when positioning their products. In particular, we highlight the importance of considering positioning relative to category prototypes and

exemplars and show that these two judgment devices are more interdependent than previous work suggests. Even if an organization is optimally balanced against one of these judgment devices, it may not be optimally positioned relative to the other. Thus, our findings suggest that organizations can potentially increase their odds of achieving optimal distinctiveness and superior performance when they use multiple judgment devices to inform entry positioning—particularly when the organization is a *de novo* entrant into a highly competitive platform ecosystem like the Google Play app store.

Second, we add to the emerging literature on strategic categorization (Cattani et al., 2017; Pontikes & Kim, 2017; Vergne & Wry, 2014). This research argues that categories are used by audiences to gain information and that organizations can strategically leverage semantic cues and categorical nomenclature in order to communicate with and help shape how consumers view them, thereby endogenously influencing and shaping consumer demand (Barroso et al., 2016). In our empirical setting, app developers choose how to describe their app, highlighting the features or characteristics that they perceive to be most important or salient, ultimately signaling to consumers how they fit within the competitive framework of a given market category. Our results show that this process has a tangible impact on the app's level of competitive advantage, both with respect to average performance and superior performance. This supports the notion that organizations can use strategic categorization “to communicate information and to position themselves favorably with respect to competitors” (Pontikes & Kim, 2017, p. 73). Our results suggest that in two-sided platform markets such as Google Play, producers can adopt strategic categorization strategies to endogenously shape and influence consumer demand within a product category. This emphasis on the

demand-side factors that shape competitive advantage is an important factor in understanding how new entrants can compete in highly competitive market spaces and offers an alternative to the supply-side perspective that focus on organization-centric factors (Barney, 1991; Eisenhardt & Martin, 2000; Teece et al., 1997).

Third, we add to the nascent and growing literature on platform ecosystems (McIntyre & Srinivasan, 2017). To date, this literature has primarily has adopted the platform as the unit of analysis and has tended to focus on either strategies a platform can adopt to achieve competitive advantage vis-à-vis rivals or strategies a platform can enact to solve the “chicken-or-the-egg” problem associated with two-sided business models (Cennamo & Santalo, 2013; McIntyre & Srinivasan, 2017; Zhu & Iansiti, 2012). Our study is among the first to specifically examine intraplatform competition among producers. We show that, in these intensely competitive environments, the entry positioning choices of de novo producers can have a substantial effect on their performance outcomes. More specifically, we show that de novo producers can increase their chances for success by identifying a category exemplar that is distant from the category prototype and positioning themselves close to this exemplar. By so doing, new producers can simultaneously increase their odds of getting noticed and avoid getting lost in the crowd.

Finally, we add to the literature on market categorization (Durand & Paoletta, 2013; Hannan et al., 2007; Hsu & Hannan, 2005; Leung & Sharkey, 2013; Negro et al., 2011; Pontikes & Kim, 2017; Vergne & Wry, 2014; Zuckerman, 1999). Specifically, we find an important boundary condition in the understanding of how and when organizations should position themselves within market categories. Typically, research

in this area suggests that organizations should fit in just enough to gain legitimacy, and then differentiate to stand out (Deephhouse, 1999). However, in our empirical setting, platform-based markets, we suggest that the ability of organizations to directly engage consumers directly through strategic categorization allows them to avoid the penalties related to deviating from the prototype for the purposes of garnering legitimacy. Instead, in these contexts, organizations can focus more on goal-based categorical associations rendering alignment with the category exemplar, and distance from the prototype, the optimal entry strategy.

This research also has important managerial implications. For example, managers would be well-advised to understand the overall competitive context of a given market category prior to entry. Focusing on a single positioning strategy relative to one judgment device is likely to be less effective than a strategy that considers multiple judgment devices. Additionally, we provide evidence suggesting that managers can take control of how information about their organization's products are communicated to consumers and that this information can be used to ultimately influence demand for these products. This can be done by utilizing semantic cues and adopting categorical nomenclatures in order to engage consumers. Ultimately, we argue that, in platform market environments, the ability of producers and consumers to iteratively and endogenously shape demand is increasingly driving competitive advantage.

This research can be generalized beyond the Google Play app store. As noted above, platform ecosystems are becoming an increasingly important part of today's economy. Platforms already create a tremendous amount of value and are operated by multibillion dollar organizations such as Airbnb, Alphabet (Google search engine,

Google Play, YouTube), Amazon, Apple (iTunes), eBay, Microsoft (X-box), Netflix, Nintendo, Sony (PlayStation), and Uber. As competition on these platforms becomes fiercer, it will become increasingly important for producers to pay close attention to their positioning choices to gain attention and avoid getting lost in the crowd. Understanding how to position products so that they appear higher in the platform's search rankings increases the probability that a product will gain attention from, and ultimately be chosen by, consumers who may tend to satisfice and stop searching once they find a suitable product that fits their needs. We see fruitful avenues for future research which tests these findings in different, nonplatform settings where producers also are able to communicate directly with consumers in an attempt to endogenously influence demand by strategically positioning themselves within a market category. Moreover, developing a deeper understanding of different types of semantic cues and nomenclatures that organizations can use to strategically categorize themselves in platform (and other) settings is an important theoretical question to unpack with important implications for helping organizations understand how to gain competitive advantage.

As with all research, there are limitations in our study that open avenues for future research. While we posit that our results generalize outside of the Google Play app store, more research is needed to substantiate our findings in other contexts. Second, while we show how developers can align their apps relative to category prototypes and exemplars, we do not fully know the extent to which producers actually consider these judgment devices when publishing a new app. Future research could build on these findings by qualitatively gauging how strategic producers are in their categorization and positioning decisions. Finally, prior research has shown that different audiences can view the same

category differently (Durand & Paoletta, 2013), so it is possible that the optimal position for critics, or other audiences, is different from the optimal position for consumers.

Future research could examine this question as well.

Table 4.1

Correlations and summary statistics

Variable	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Review Count (ln)	3.06	2.06	-4.61	15.55																
(2) Prototype Similarity	0.22	0.13	0.00	1.00	0.01															
(3) Exemplar Similarity	0.33	0.17	0.00	1.00	0.16	0.56														
(4) Category Density (*10 ⁻³)	72.06	45.94	1.19	173.97	-0.08	-0.23	-0.20													
(5) Category Contrast	0.21	0.05	0.14	0.36	0.07	0.36	0.33	-0.49												
(6) Developer Category Spanning	1.38	0.80	0.00	9.00	-0.10	0.08	0.10	-0.05	0.09											
(7) Uses Category Names	0.45	0.50	0.00	1.00	0.08	0.26	0.28	-0.37	0.33	0.06										
(8) Percent Developer Apps w/ Category Names	37.58	42.16	0.00	100.00	0.07	0.21	0.24	-0.33	0.28	0.06	0.86									
(9) Review Average (lag)	4.28	0.72	0.00	5.00	-0.13	0.00	-0.04	0.02	-0.03	-0.04	0.00	-0.01								
(10) App Age (days)	236.27	132.78	0.00	571.00	0.04	-0.02	-0.07	0.10	0.00	-0.06	-0.02	-0.06	-0.08							
(11) Free App	0.96	0.20	0.00	1.00	0.12	0.04	0.02	0.01	-0.06	0.06	0.01	0.01	-0.02	-0.02						
(12) Offer In-App Purchases	0.12	0.32	0.00	1.00	0.17	0.02	0.06	-0.13	0.10	-0.04	0.16	0.14	-0.01	-0.02	0.03					
(13) Cleansed Description length (char)	486.58	416.53	0.00	4636.00	0.15	-0.09	0.20	-0.04	0.01	-0.05	0.19	0.19	-0.04	-0.06	-0.08	0.12				
(14) App Size (MB)	13.20	34.46	0.00	2355.20	0.08	-0.02	0.00	-0.10	0.05	-0.03	0.12	0.11	0.00	-0.01	-0.10	0.15	0.08			
(15) App Entry Order	1.63	1.29	0.00	10.00	-0.09	0.07	0.09	0.01	0.08	0.45	0.04	0.03	-0.10	-0.08	0.03	-0.06	-0.01	-0.03		
(16) Changes Description	0.35	0.48	0.00	1.00	0.16	0.00	0.04	-0.02	0.02	-0.07	-0.01	-0.02	0.01	0.08	-0.06	0.06	0.09	0.02	-0.06	
(17) Developer Enters with >1 App	0.46	0.50	0.00	1.00	-0.12	0.11	0.11	0.00	0.12	0.50	0.05	0.01	-0.08	-0.06	-0.02	-0.07	-0.06	-0.04	0.53	-0.06

Table 4.2

GEE regression models with robust standard errors clustered at the developer level;
dependent variable is log review counts.

VARIABLES	Model 1	Model 2	Model 3
Prototype Similarity (centered)		-0.700 [0.089] (0.000)	-0.663 [0.089] (0.000)
Exemplar Similarity (centered)		0.780 [0.070] (0.000)	0.793 [0.070] (0.000)
Prototpye Sim. X Exemplar Sim.			-1.003 [0.361] (0.006)
Category Density (*10⁻³, centered)	0.000 [0.000] (0.265)	0.000 [0.000] (0.221)	0.000 [0.000] (0.213)
Category Contrast	1.616 [0.360] (0.000)	1.598 [0.361] (0.000)	1.610 [0.361] (0.000)
Developer Category Spanning	-0.191 [0.012] (0.000)	-0.193 [0.012] (0.000)	-0.193 [0.012] (0.000)
App Uses Category Name	-0.024 [0.024] (0.320)	-0.034 [0.025] (0.172)	-0.036 [0.025] (0.147)
Percent Developer Apps w/ Category Names	0.001 [0.000] (0.000)	0.001 [0.000] (0.000)	0.001 [0.000] (0.000)
Review Average (lagged)	-0.184 [0.010] (0.000)	-0.183 [0.010] (0.000)	-0.183 [0.010] (0.000)
App Age (days)	0.001 [0.000] (0.000)	0.001 [0.000] (0.000)	0.001 [0.000] (0.000)
Free App	1.669 [0.041] (0.000)	1.662 [0.041] (0.000)	1.662 [0.041] (0.000)
Offer In-App Purchases	0.458 [0.033] (0.000)	0.456 [0.033] (0.000)	0.455 [0.033] (0.000)
Cleansed Description Length (characters)	0.001 [0.000] (0.000)	0.001 [0.000] (0.000)	0.001 [0.000] (0.000)
App Size (MB)	0.002 [0.000] (0.000)	0.002 [0.000] (0.000)	0.002 [0.000] (0.000)

Table 4.2 continued

VARIABLES	Model 1	Model 2	Model 3
App Entry Order	-0.026 [0.006] (0.000)	-0.026 [0.006] (0.000)	-0.026 [0.006] (0.000)
Changes Description	0.405 [0.021] (0.000)	0.402 [0.021] (0.000)	0.402 [0.021] (0.000)
Developer Enters with >1 App	-0.295 [0.018] (0.000)	-0.305 [0.018] (0.000)	-0.304 [0.018] (0.000)
Category Fixed Effects	<i>Included</i>	<i>Included</i>	<i>Included</i>
Wave Fixed Effects	<i>Included</i>	<i>Included</i>	<i>Included</i>
Constant	1.107 [0.105] (0.000)	1.171 [0.105] (0.000)	1.184 [0.105] (0.000)
Observations	470,728	470,728	470,728
Number of Developers	82,149	82,149	82,149
chi2	27261	27436	27451
p	0	0	0
QIC	1,729,571	1,707,863	1,706,729

Note: Robust standard errors clustered at the developer level in brackets; p -value in parentheses.

Table 4.3

Logistic regression models with robust standard errors clustered at the developer level;
dependent variable is a binary indicator for apps reaching 100,000 or more downloads.

VARIABLES	Model 1
Prototype Similarity (centered)	-1.338 [0.178] (0.000)
Exemplar Similarity (centered)	2.752 [0.110] (0.000)
Prototype Sim. X Exemplar Sim.	-1.791 [0.662] (0.007)
Controls	<i>Included</i>
Category Fixed Effects	<i>Included</i>
Wave Fixed Effects	<i>Included</i>
Constant	-3.976 [1.259] (0.002)
Observations	107,106
Pseudo R-Squared	0.133
Log Likelihood	-18,268

Note: Robust standard errors clustered at the developer level in brackets; p -value in parentheses.

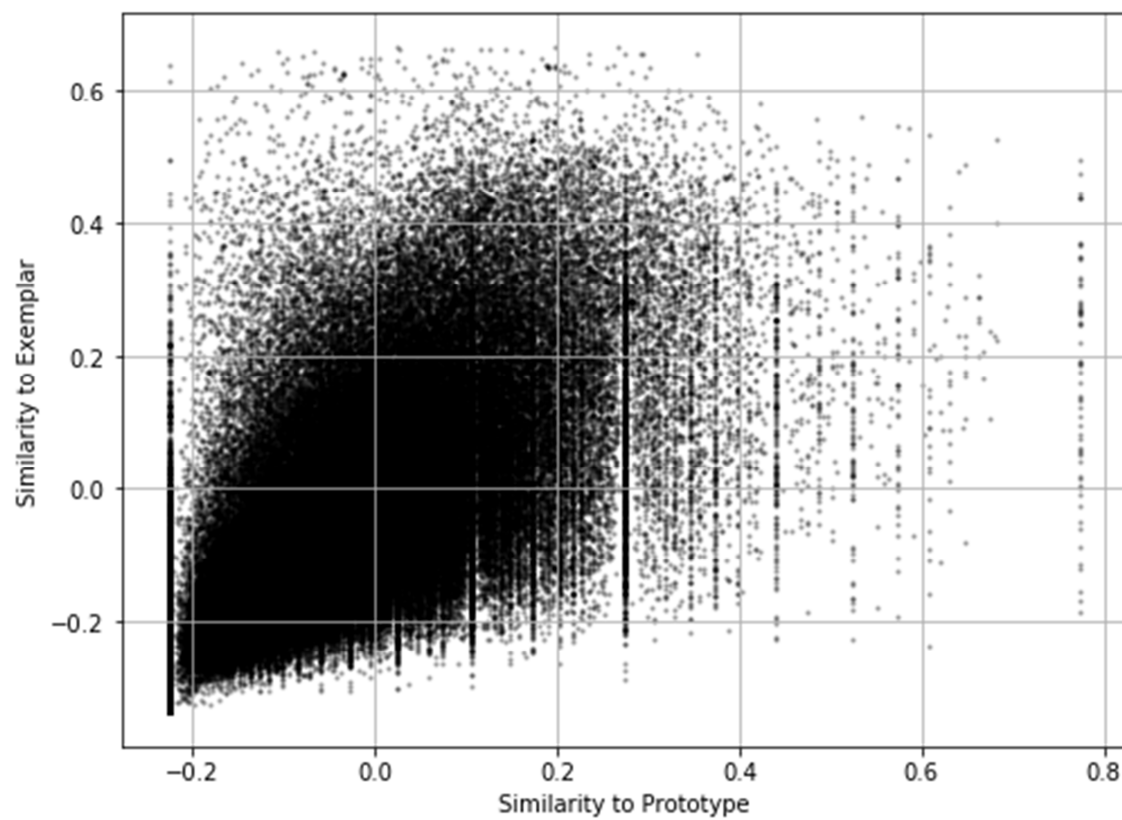


Figure 4.1 Scatterplot of similarity to the category prototype (centered) versus similarity to a category exemplar (centered).

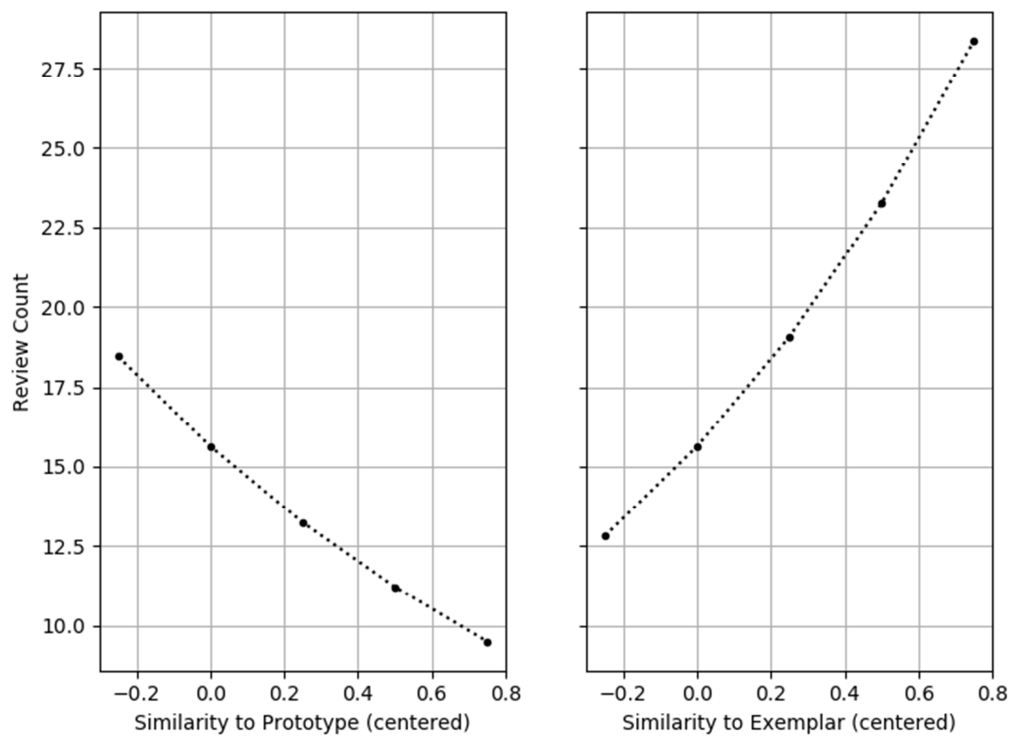


Figure 4.2 Performance analysis (predicted review count) for various levels of similarity to the category prototype category and to an exemplary category member.

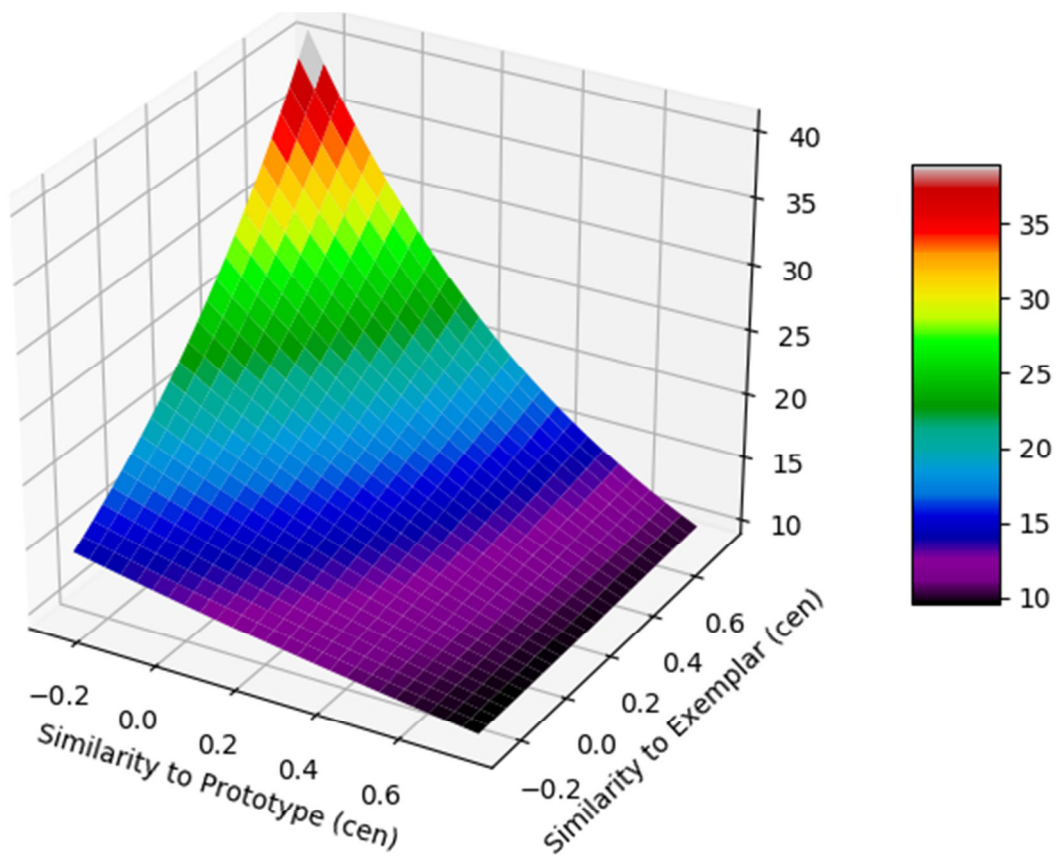


Figure 4.3 3-Dimensional plot showing app average predicted performance (review count) versus both prototypical and exemplar similarity scores (centered).

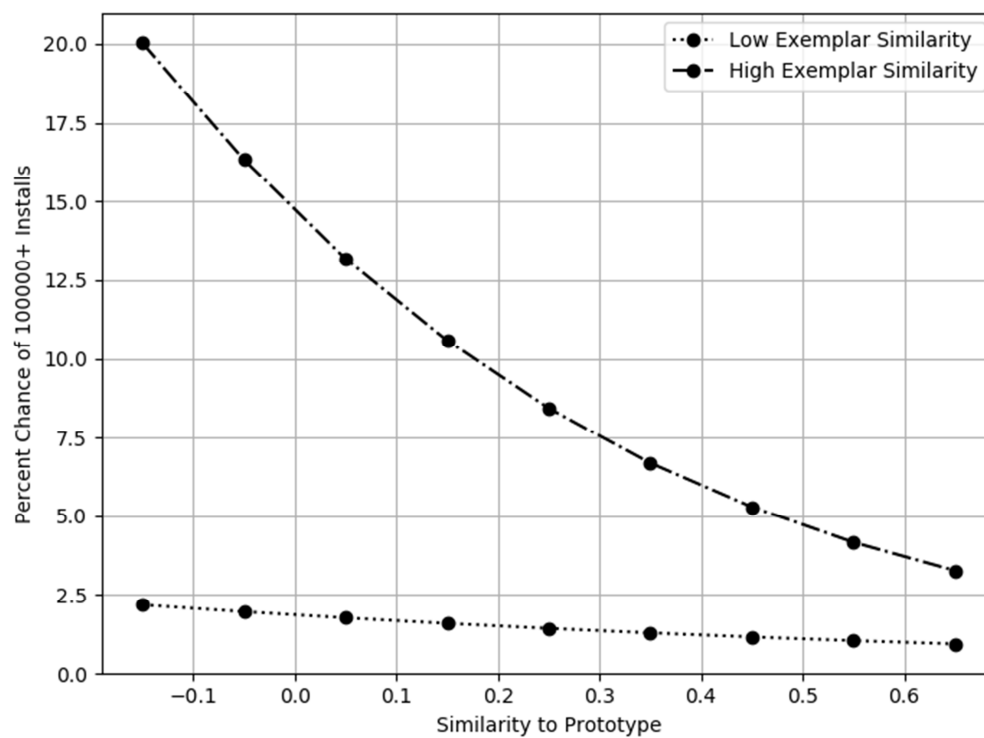


Figure 4.4 Probability of achieving 100,000 or more downloads by prototypical and exemplar similarity scores (centered). Low exemplar similarity = -0.15 (centered); high exemplar similarity = 0.65 (centered).

CHAPTER 5

CONCLUSION

In this dissertation, three essays were presented which shed light on how entrepreneurs create value through the introduction of new products and services under conditions of uncertainty. This research contributes to a growing body of entrepreneurship and strategic management scholarly work investigating the process of value creation.

The first essay theoretically examines entrepreneurial stakeholder enrollment. Most entrepreneurial endeavors do not initially possess all of the resources they need to successfully create a valuable opportunity. Some of the needed resources can be acquired through simple contracts. However, other resources require the resource provider to provide a level of effort that goes beyond that which is contractible. Such efforts often require the resource provider to form deep psychological bonds with the entrepreneurial endeavor. Stakeholder enrollment is the process of forming these bonds with entrepreneurial endeavors. The target of these bonds can be either the entrepreneur herself or the entrepreneurial opportunity being pursued. In entrepreneurial settings, these bonds are typically formed under conditions of risk or uncertainty. Under both risk and uncertainty, information about the entrepreneur's experience, reputation, personality, trustworthiness, charisma, and leadership style is available to stakeholders. However, one

important difference between these conditions is that, under risk, information about the value of the opportunity is available to stakeholders whereas under uncertainty, this information is not available. Thus, this essay first proposes that under conditions of risk, the initial target with which a stakeholder forms psychological bonds can be the entrepreneur, the opportunity, or a combination of both. The essay then proposes that under conditions of uncertainty, the initial target with which a stakeholder forms psychological bonds should be the entrepreneur—not the opportunity. These propositions generate important implications for scholars and practitioners alike. For example, one practical implication is that under conditions of uncertainty, the opportunity is likely to evolve and change substantially during the creation process. If stakeholders enroll in an uncertain opportunity (instead of enrolling in the entrepreneur), then each time entrepreneurs engaged in a “pivot,” they would have to re-enroll stakeholders. This implication leads directly into the second essay.

The second essay empirically examines entrepreneurial pivoting. Pivoting is widely believed to be an important ingredient for entrepreneurial success under conditions of uncertainty. However, it remains unclear how far entrepreneurs do—and should—pivot to improve their chances of successfully creating value. This essay draws on problemistic search and resource-based theory to empirically examine entrepreneurial pivoting in the context of the Google Play app store. This empirical context allows for the construction of a continuous measure of pivot distance using text-based analysis. Consistent with problemistic search theory, the lower the performance (installs) of a developer’s first app, the further the developer will pivot for its second app. And, consistent with resource-based theory, pivot distance negatively moderates the

relationship between app one installs and app two installs. Further analysis reveals that this moderating effect of pivot distance takes an inverted-u form: minor pivots outperform major pivots and not pivoting at all. Taken together, these findings suggest that app development entrepreneurs tend to “over-pivot” in response to negative performance feedback and that over-pivoting has a negative effect on performance. These findings highlight the need for caution when advising entrepreneurs to pivot without noting the potentially harmful effects of pivoting too far.

The third essay empirically examines how entrepreneurial organizations competing on a two-sided platform can position new products to maximize value creation. Platforms, such as internet search engines, Amazon, Netflix, Uber, Airbnb, video game consoles, YouTube, eBay, iTunes, and the Google Play app store are important competitive environments in today’s economy. At least two arguments for how a de novo organization should position its new products on platforms can be derived from the extant literature. On the one hand, some work suggests that entrepreneurs should conform by positioning new products in a way that is similar to other products in a market category to obtain the benefits of legitimacy. On the other hand, another body of work suggests that entrepreneurs should differentiate by positioning new products in a way that is different from other products to obtain a competitive advantage. As a result, de novo organizations competing on a two-sided platform often face uncertainty regarding how to position their products within a market category. Furthermore, prior work does not clearly articulate which other products within a market category should be used as reference points when making this conformity versus differentiation decision. This essay argues that there are two important judgment devices that organizations can

use to strategically categorize themselves within product market categories: the prototypical category member and the exemplar category member. Using a unique dataset from the Google Play mobile application store, this essay finds that the optimally distinct point for a de novo developer's first app is at low levels of similarity to the prototypical app, but at high levels of similarity to an exemplar app. Moreover, the essay finds that prototype similarity negatively moderates the positive effect of exemplar similarity such that the more an organization aligns with the prototype, the more the organization loses the competitive advantage gained from similarity to the exemplar. The findings have important implications for our understanding of competitive dynamics within and across product markets, strategic positioning at the time of market entry, and the interdependence of strategic categorization decisions.

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